Coping with Change in Markets, the Workplace and Communities

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Jano Costard, M.Sc.

Präsidentin der Humboldt-Universität zu Berlin:
Prof. Dr.-Ing. Dr. Sabine Kunst

Dekan der Wirtschaftswissenschaftlichen Fakultät
Prof. Dr. Christian D. Schade

Gutachter: 1. Prof. Dr. Roland Strausz
2. Prof. Dr. Steffen Huck

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Preface

Change comes with opportunities but also risks for the people or organizations affected. Due to this complexity, many people seek to influence the direction of change they are subject to. However, since their future is influenced by various factors and is hence inherently uncertain, it is often not clear which options are most promising. In this dissertation, I study change in three different settings, namely in a market environment, at the workplace and within communities. Making use of the economist's toolbox, theoretical models and experiments enable the identification of cause and effect of actions while change takes place.

In Chapter 1, I study formerly large and successful firms whose failure can be linked to the emergence of a new market. This new market uses the same technology as the old market. It is therefore puzzling why firms who were proven industry leaders failed in markets that require the same technological skills. Chapter 2 analyzes the impact of disadvantageous and preferential treatment in the workplace. To this end, we conduct a sequence of experiments in which participants are paid to solve tasks. In these experiments, we compare the effects of (dis)advantageous treatment in terms of wage and workload on performance and use facial expression analysis software to link people's facial expressions with future performance. Finally, Chapter 3 studies to what extent people condition the extend to which they show solidarity on other people's level of risk taking.

New Markets and the Failure of Old Firms

The paper "New Markets and the Failure of Old Firms" takes the literature on industry evolution(see e.g. Gort & Klepper, 1982; Jovanovic, 1982; Jovanovic & MacDonald, 1994; Klepper, 1996, 2002) as point of departure. This literature can successfully explain many stylized facts of markets' evolution. However, these models are not readily reconcilable with the observation that industry leaders that entered their industries early on and were very innovative suddenly go extinct when new markets emerge that use the same technology. To solve this puzzle, I extend one class of models of industry evolution by explicitly allowing for the arrival of a second market. I show that the failure of successful and innovative firms from the old market is based on two potential explanations: 1) The goods sold in the old and new market could be such close substitutes that firms from the old market opt not to enter the new market of fear for cannibalizing their original product, 2) The firms are characterized by organizational diseconomies of scope, i.e. a cost disadvantage of being active in both markets.

To gain a better understanding of the importance of the two effects, I conduct three case studies of former industry leaders that failed upon the arrival of new markets in which they had a technological advantage. Those are Digital Equipment Corporation, Metro-Goldwyn-Mayer and Kodak. All three firms differ substantially but all three firms struggled due to organizational diseconomies of scope and not due to substitution effects. Although I discuss several potential reasons for organizational diseconomies of scope, I also identify the need for further research in this regard. The following project was inspired by the lack of understanding of organizational diseconomies of scope in change processes.

Emotions and Effort

“Emotions and Effort”, a joint project with Steffen Huck, asks a question that has received attention from economists and psychologists alike (see e.g. Akerlof & Yellen, 1990; Spector, 1978): How do work conditions affect workers’ behavior? In a controlled laboratory setting, we conduct a sequence of experiments in which we investigate how social comparison impacts workers’ productivity in the context of reallocating wages or workload. Social comparison is especially interesting in our setting, as all experiments are characterized by the fact that high skilled participants face a disadvantageous treatment whereas worse performing participants receive preferential treatment. By studying both changes in wage and changes in workload, we are able to determine whether one is preferable to the other in terms of efficiency.

In addition, we employ facial expression analysis software. This way we are able to link the facial expression of emotion triggered by the announcement of change to future productivity. In doing so, we study one important aspect of change: How could negative responses to change be foreseen? What is more, a questionnaire at the end of the experiment provides us with additional information on participants’ dealing with emotion.

The participants in our experiments react with reduced effort to being informed that worse performing participants are exempt from an increase in workload at constant wage. At the same time, they do not react negatively in terms of emotion. In contrast, low skill participants that are informed of their preferential treatment show more anger in response to this information. In addition, this increased anger is associated with increased productivity. These results, however, are not robust with regard to variations in the treatment, i.e. no treatment effect in terms of productivity can be found if less skilled participants receive easier tasks or the unequal treatment is based on a difference in wages. This is despite the fact that questionnaire measures of anger as well as comments in open questions at the end of the experiment and anecdotal evidence from the laboratory indicate that disadvantaged high skill participants got angry in response to the treatment.

Solidarity, Responsibility and In-Group Bias

In "Solidarity, Responsibility and In-Group Bias", Friedel Bolle and I investigate two conflicting motives in showing solidarity. On the one hand, it has been shown that people are held responsible for their actions (see e.g. Cappelen, Sørensen, & Tungodden, 2010). On the other hand, people often engage in in-group/out-group discrimination (see e.g. Tajfel, 1970).

We conduct an experiment to study the relative importance of these two factors in showing solidarity. Participants chose between two lotteries A and B. Lottery A has a lower probability of paying nothing than lottery B. However, lottery B pays a larger prize in case of a win. Before subjects chose a lottery they know that a phase of voluntary redistribution in groups of three follows the lottery choice. Due to this redistribution, the winners of a lottery can show solidarity towards the losers. Crucially, winners of a prize can make transfers conditional on the lottery choice of the losers. While holding people responsible for their lottery choice suggests that losers who chose lottery B and therefore did not avoid risk receive less solidarity, in-group favoritism predicts that the same participants are only discriminated against by winners of the less risky lottery A.

Indeed, in our experiment we find in-group bias. People who win a prize in the less risky lottery show less solidarity towards losers who chose the more risky lottery. This result is in line with both holding people responsible for their actions and in-group bias. However, winners of lottery B show more solidarity towards loser who also chose lottery B than towards loser who chose the less risky lottery A.

Further, we extend the fairness theory of Cappelen, Konow, Sørensen, and Tungodden (2013) and show that differences in the acceptance of risk are associated with different views on fairness. While many participants from both groups can be thought of as being supportive to their own kind, a quarter of participants who avoided risk conform with behavior that aims at equalizing payoff unconditionally. In contrast, the share of more risk accepting participants that aim at equalizing payoff for all is zero.

Chapter 1

New Markets and the Failure of Old Firms*

1.1 Introduction

Market conditions are not constant but subject to change. In particular, newly arising markets that emerge due to new inventions are subject to change. Over time, more firms enter the market, production increases and prices fall (see e.g. Gort and Klepper (1982)). This evolution of markets has been modeled and empirically analyzed by Jovanovic (1982); Jovanovic and MacDonald (1994); Agarwal and Gort (1996) and Klepper (2002) amongst others (for an overview see Malerba, 2007).

One additional aspect of some markets' development is a decrease of the number of active firms after an initial increase; a pattern called shake out. Based on the above mentioned existing models, different firm characteristics can be identified, which make it less likely for firms to be part of the shake out. Among these are entering a market early on and being highly innovative (Klepper, 2002; Jovanovic & MacDonald, 1994) or efficient (Jovanovic, 1982).

However, while the literature on the evolution of markets can successfully explain the stylized facts of many markets' developments there are prominent counter examples of firms that have been technologically superior industry leaders for decades but failed nevertheless. These failures can be linked to the arrival of new markets but they occurred despite the fact that these emerging markets used the same technology as the old market. What is more, according to the predictions of the above cited models large and innovative firms should actually

*Over the course of the research for this paper, I received important feedback from many people. In particular, I would like to thank Roland Strausz, Steffen Huck, Volker Nocke, Jana Friedrichsen, Sebastian Schweighofer-Kodritsch and Pio Baake for their comments.

have an advantage in these emerging markets.

In this paper, I attempt to resolve the puzzle of failing old and formerly large and successful firms. I show that their failure can be understood in light of an extended model of industry evolution. I complement the theoretical analysis with three case studies of failed former industry leaders.

In particular, I extend the Klepper (2002) model by explicitly including the emergence of a second market. Based on the extended framework two potential causes for failure connected to the emergence of a second market can be identified: a cannibalization effect and organizational diseconomies scope. The first is based on strategic considerations according to which a firm might have lower incentives to supply a good that is a substitute to another of its products while this effect is absent in firms that are active in only one of the markets. The second potential cause lies in organizational diseconomies of scope that make it more expensive to grow in one market if the firm is also active in another market. While the first effect seems to be well understood by economists, the second might be less familiar. To gain a better understanding of the potential role and relative strength of these two effects, the case studies describe the rise and fall of Kodak, Digital Equipment Corporation and Metro-Goldwyn-Mayer. All firms share the characteristic that they entered their original market early on and were successful innovators which made them large and highly profitable firms for decades. However, they also share a rapid downturn of their business and finally failure. These failures are connected to the arrival of new markets such as digital photography, the IBM compatible PC and TV. Yet, all three firms had a technological advantage in these markets. Kodak for example invented digital photography. Based on the above models of industry evolution, it is a puzzle why these firms failed upon the arrival of markets where they had a technological advantage over new firms. Interestingly, the three cases point at organizational diseconomies of scope as a prime reason for their failure. These seem to outweigh the technological superiority of the experienced firms.

The paper is organized as follows. In Section 1.2, I introduce the model of industry evolution and the emergence of a second markets. Section 1.3 includes the case studies on the rise and fall of Digital Equipment Corp., Metro-Goldwyn-Mayer and Kodak, Section 1.4 discusses other theories of industry evolution and potential causes for organizational diseconomies of scope and Section 1.5 concludes.

1.2 Model

In this section, a model of a market's evolution will be presented. Based on the model, predictions concerning the development of market price and the number of firms active in the market can be derived. In particular, it will be shown that old firms with highly effective R&D are least likely to leave the market. In a second step, the emergence of a second, related market is analyzed and it is shown how those firms' advantage in the first market can translate into a disadvantage in the new market.

1.2.1 A market's evolution

The market to be analyzed is born in $t = 1$ and inhabited by firms and consumers who take actions in discrete time. Each period consists of four stages. In stage 1, K potential entrants are presented the opportunity to enter the market. In stage 2, incumbent firms decide whether to exit the market or stay active and potential entrants decide on whether to enter or not. Next, firms chose their level of R&D investment and in stage 4 firms set quantities (see Figure 1.1).

All firms are assumed to supply a homogeneous product to consumers that are characterized by inverse demand function $P(Q_t)$ that is decreasing and concave in the aggregate quantity produced by all firms, Q_t. R&D is modeled as process innovation in the sense that it is cost reducing. In particular, a firm's production cost consists of a common cost component c_t that is reduced by $\alpha_i g(r_{it})$, the fruit of cost reducing R&D. Here, $g(r_{it})$ is the production function of R&D, which is increasing and concave in the investment in R&D, r_{it}, and generates costs of r_{it}. $g(r_{it})$ is augmented by factor α_i which captures different levels in skill of conducting R&D, i.e. $\alpha_i > \alpha_j > 0$ for a firm i of type $\theta_i = H$, the highly innovative type, and a firm j of less innovative type $\theta_j = L$. Among the K potential entrants, a share $s > 0.5$ is of the less innovative type. Following Klepper (2002), innovation is assumed to be imitated at no cost with a one period lag. Therefore, the common cost component c_t is given by

$$c_t = c_{t-1} - \max_i \{\alpha_i g(r_{it-1})\}$$

with $c_1 > 0$ and such that both types of firms can profitably enter in $t = 1$[2]. In addition, firms face a cost $m(\Delta Q_{it}; Q_{it-1})$ that depends on the time difference in output $\Delta Q_{it} = Q_{it} - Q_{it-1}$ and reflects costs of adaptation and scarcity of resources when a firm expands. $m(\cdot)$ is increasing and convex in ΔQ_{it} for $\Delta Q_{it} > 0$ and zero otherwise. Also, $m(\cdot)$ as well as $\partial m(\cdot)/\partial Q_{it}$ is decreasing in Q_{it-1}. Based on the above, firms chose quantity Q_{it}, investment in R&D r_{it} and their entry/exit decision so as to maximize current period profit Π_{it} given by

$$\Pi_{it} = [P(Q_t) - c_t + \alpha_i g(r_{it})]Q_{it} - r_{it} - m(\Delta Q_{it}; Q_{it-1}) \qquad (1.1)$$

[2]The market dies at T with T such that $\sum_{t=1}^{T} \alpha_i g(r_{it}) = c_1$ for a high type firm i that entered the market in $t = 1$.

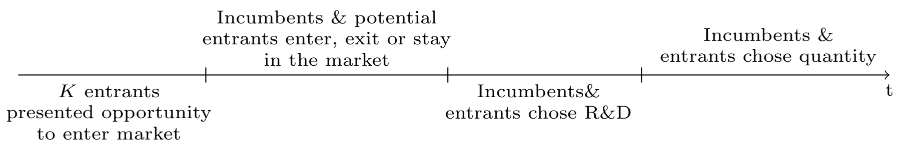

Figure 1.1: Structure of the game in period t.

In the last stage of each period, when incumbents and potential entrants set quantities, their profit maximizing level, Q_{it}, solves the first order condition of Equation 1.1 with respect to Q_{it}, given by

$$P(Q_t) + P'(Q_t)Q_{it} - c_t + \alpha_i g(r_{it}) = m'(\Delta Q_{it}; Q_{it-1})$$

if this quantity is positive. Otherwise the quantity is set at zero. As the profit function of every firm i is strictly concave in Q_{it} a Nash equilibrium of this Cournot game exists and is unique. Taking the derivative of Equation 1.1 with respect to r_{it} gives the first order condition

$$\alpha_i g'(r_{it})Q_{it} = 1$$

which is solved by the incumbents' and potential entrants' optimal r_{it} for $Q_{it} > 0$[3]. Otherwise, $r_{it} = 0$.

Lastly, incumbents for which $\Pi_{it} > 0$ stay in the market and exit otherwise and potential entrants for which $\Pi_{it} > 0$ enter and all others abstain.

Based on the first order conditions of profit maximization it can be seen that each firm's quantity Q_{it} is increasing in its effectiveness of R&D, α_i, increasing in the margin of price over the common cost component c_t and increasing in Q_{it-1}. In addition, the investment in cost reducing R&D is increasing in α as well as in the quantity to which it applies, Q_{it}.

In this setup, two factors contribute to firm heterogeneity. First, high type firms have larger price-cost margins and therefore bring larger quantities to the market than low type firms. Second, due to the cost of growth, the time of entry matters. In particular, later entrants have a disadvantage over earlier entrants of the same type they cannot make up for because they will bring smaller quantities to the market which also translates into lower investment in R&D and therefore lower margins. This is despite the fact that R&D can costlessly be imitated with a one period lag.

R&D spillovers contribute to an industry-wide cost reduction in each period. As a consequence, the market exhibits an increasing aggregate quantity over

[3]Here, investment in R&D is conducted with the aim of cost reduction only and not for strategic purposes. In this sense, it is rather a Dasgupta and Stiglitz (1980) world than one of Brander and Spencer (1983).

time and a falling market price. It is important to note, though, that this development occurs although some firms might reduce their quantities from one period to the next. A pattern that occurs if the market price drops sufficiently so as to make it prohibitively expensive for a firm to incur a cost of quantity growth.

Lemma 1. *Aggregate quantity Q_t is strictly increasing in t and the price $P(Q_t)$ is strictly decreasing over time.*

Proof. Suppose firm i reduces its quantity supplied in period t such that it offsets the quantity increase by all other firms, i.e. $Q_{it} = Q_{it-1}$. As a consequence, it will choose Q_{it} such that

$$P(Q_t) + P'(Q_t)Q_{it} > c_t - \alpha_i g(r_{it}) + m'(\Delta Q_{it}; Q_{it-1}).$$

A contradiction. This is due to the fact that in comparison with period $t-1$ where

$$P(Q_{t-1}) + P'(Q_{t-1})Q_{it-1} = c_{t-1} - \alpha_i g(r_{it-1}) + m'(\Delta Q_{it-1}; Q_{it-2})$$

$P(Q_t) = P(Q_{t-1})$, $P'(Q_t)Q_{it} > P'(Q_{t-1})Q_{it-1}$ because $P'(Q_t) = P'(Q_{t-1})$ and $Q_{it} < Q_{it-1}$, $m'(\Delta Q_{it}; Q_{it-1}) \leq m'(\Delta Q_{it-1}; Q_{it-2})$ and, crucially, $c_t - \alpha_i g(r_{it}) < c_{t-1} - \alpha_i g(r_{it-1})$ as $c_t < c_{t-1}$ and $\alpha_i g(r_{it}) < \alpha_i g(r_{it-1})$.

As inverse demand is strictly decreasing and time constant and aggregate quantity strictly increasing over time, the price $P(Q_t)$ is strictly decreasing over time. □

Over time, the downward trend in prices can lead to a situation in which it becomes unprofitable for additional firms to enter the market. In particular, entry is not profitable for entrant i if for $Q_{it} > 0$

$$P(Q_t) + P'(Q_t)Q_{it} - c_t + \alpha_i g(r_{it}) < m'(\Delta Q_{it}; 0)$$

This is to say that a pair Q_{it}, r_{it} larger than zero is too expensive to achieve. As high type firms have a larger effectiveness of cost reducing R&D it follows that high type firms will not stop entering the market before low type firms do.

Similarly, a firm that has been active in the market exits if the market price $P(Q_t)$ falls below the common cost component c_t and it is prohibitively expensive for that firm to generate a large enough cost reduction through R&D so as to arrive at positive price-cost margins. This is exactly the condition under which the market will experience a reduction in the number of firms: a shakeout.

Proposition 1. *A shakeout occurs if and only if for some firm i in period t*

$$P(Q_t) - c_t < m'(\Delta Q_{it}; Q_{it-1}) - \alpha_i g(r_{it}) - P'(Q_t)Q_{it} \tag{1.2}$$

for all $Q_{it} > 0$

Proof. Note that the exit of one firm is equivalent to a reduction in the total number of firms in the market. To see this consider the two cases 1) a low type firm exits and 2) a high type firm exits the market. For 1), if a low type firm leaves the market it cannot be that other low type firms still enter the market as Q_{it} is increasing in Q_{it-1}. In contrast, entry by high type firms could still occur. Nevertheless, as all firms of the same type that entered in the same period are identical and therefore also leave the market in the same period and the number of potential entrants is constant over time and the share of low type firms among potential entrants is larger than 1/2, the exit of a cohort of low type firms will, in numbers, outweigh any potential entry by high type firms. For 2), in case high type firms exit, there cannot be entry anymore. Therefore, exit by high type firms directly translates into a reduction of the total number of firms in the market.

if: The above condition states that for firm i in period t marginal revenue is smaller than marginal cost of production for all $Q_{it} > 0$. i's best response to the output of all other firms, Q_{-it} is therefore to set $Q_{it} = 0$ and exit the market.

only if: Firm i will only leave the market in period t if $\Pi_{it} \leq 0$. As there are no fixed costs involved and Π_{it} is concave, this is equivalent to the first order condition with regard to Q_{it} being negative for all $Q_{it} > 0$, i.e.

$$P(Q_t) + P'(Q_t)Q_{it} - c_t + \alpha_i g(r_{it}) - m'(\Delta Q_{it}; Q_{it-1}) < 0$$

□

It follows that a necessary condition for a shakeout is given by the market price in period t falling below the average cost of production of the most efficient firm in period $t-1$. As there is exit only if $P(Q_t) - c_t < 0$ and $c_t = c_{t-1} - max_i\{\alpha_i g(r_{it-1})\}$ it follows that $P(Q_t) < c_{t-1} - max_i\{\alpha_i g(r_{it-1})\}$ is necessary for exit.

Corollary 1. *A shakeout occurs only if the market price in period t falls below the average cost of production of the most efficient firm in period $t-1$, i.e.*

$$P(Q_t) < c_{t-1} - max_i\{\alpha_i g(r_{it-1})\}$$

In addition, the RHS of Equation 1.2 is decreasing in the age of the firm as $m'(\Delta Q_{it}; Q_{it-1})$ is decreasing in Q_{it-1}. Similarly, the RHS is decreasing in α_i. Therefore, the condition in Equation 1.2 will be satisfied for younger and less innovative firms before the same is true for older more innovative firms.

Corollary 2. *If old and highly innovative firms exit the market, they do so not before younger and less innovative firms left the market.*

As a consequence, a high skill in innovation and a head start through early entry bring benefits to a firm that later entrants or less skillful innovators cannot achieve. In particular, high type firms that entered in $t = 1$ will not be driven out of the market. However, what has been an advantage in one market, might become a disadvantage if a new market arrives. The next section analyzes such a case.

1.2.2 Emergence of a related market

In the previous section, I describe how a market can change with regard to its size and composition. Besides the change within markets, often industries are subject to change due to new inventions which create new markets as well.

I assume that a new market occurs at an exogenously given point in time. Firms active in this new market produce a good called b in contrast to the good produced in the original market, called a. Products a and b have some proximity in the sense that consumers perceive goods a and b as (imperfect) substitutes, i.e. $\partial P^a(Q_t^a, Q_t^b)/\partial Q_t^b < 0$ and $\partial P^b(Q_t^b, Q_t^a)/\partial Q_t^a < 0$. Just as in the single market, inverse demand is concave in quantity. Further, for $k, l \in \{a, b\}$ and $k \neq l$ I assume that $\partial^2 P^l(Q_t^l, Q_t^k)/\partial Q_{it}^l \partial Q_{it}^k \leq 0$, i.e. the slope of the inverse demand of one good is not increasing in the quantity supplied of the other good.

To consider the case where firms from the original market have a technological advantage in the new market, I assume that firms' R&D expenditure for product a can be of use as well for product b. In fact, I will make the extreme assumption that R&D is a pure public input in the sense that for a firm producing goods a and b an investment of r_{it} invested in R&D produces a cost reduction of $\alpha_i g(r_{it})$ in both markets.

In addition, a firm that produces goods a and b incurs a cost of growing output captured by $m(\Delta Q_{it}^k, \Delta Q_{it}^l; Q_{it-1}^k, Q_{it-1}^l)$. Equivalent to the case of one market, I assume that $m(\Delta Q_{it}^k, \Delta Q_{it}^l; Q_{it-1}^k, Q_{it-1}^l) = 0$ for $\Delta Q_{it}^k \leq 0$ and $\Delta Q_{it}^l \leq 0$. Otherwise, $m(\Delta Q_{it}^k, \Delta Q_{it}^l; Q_{it-1}^k, Q_{it-1}^l) > 0$. In addition, $m(\Delta Q_{it}^k, \Delta Q_{it}^k; Q_{it-1}^l, Q_{it-1}^l)$ is increasing and convex in ΔQ_{it}^k and ΔQ_{it}^l. Further, there are economies of scope if $\partial^2 m(\Delta Q_{it}^k, \Delta Q_{it}^l; Q_{it-1}^k, Q_{it-1}^l)/\partial Q_{it}^k \partial Q_{it}^l <$ 0 and there are diseconomies of scope if $\partial^2 m(\Delta Q_{it}^k, \Delta Q_{it}^l; Q_{it-1}^k, Q_{it-1}^l)/\partial Q_{it}^k \partial Q_{it}^l$

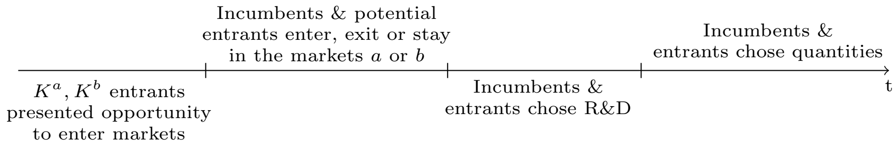

Figure 1.2: Structure of the game in period t for the case of two markets.

> 0 and it is assumed that $\partial^2 m(\Delta Q^k_{it}, \Delta Q^l_{it}; Q^k_{it-1}, Q^l_{it-1})/\partial Q^k_{it}\partial Q^l_{it} \in (m_-, m_+)$ with $m_- < 0 < m_+$[4]. Note that in Klepper (2002) it is implicitly assumed that the marginal cost of growth is independent of the quantity produced of the other good for firms that have been active in another market before entry.

The structure of the game to be played is very similar to the one where there is just one market and is depicted in Figure 1.2. A finite number K^a of potential entrants and a finite number K^b of potential entrants is presented the opportunity to enter markets a and b whereas every incumbent in market a is a potential entrant in market b and both, high and low type entrants, can profitably enter the new market. After having made their entry or exit decision, firms set their level of R&D investment and set their quantity or quantities.

Apart from the second market and the resulting (dis)economies of scope, the firms' maximization problem is the same as before. A firm i's profit function depending on whether it is active only in market a, only in market b or active in both markets, is given by

$$\begin{aligned}
\Pi^a_{it} &= [P^a(Q^a_t, Q^b_t) - c^a_t + \alpha_i g(r^a_{it})]Q^a_{it} - r^a_{it} - m(\Delta Q^a_{it}; Q^a_{it-1}) \\
\Pi^b_{it} &= [P^b(Q^b_t, Q^a_t) - c^b_t + \alpha_i g(r^b_{it})]Q^b_{it} - r^b_{it} - m(\Delta Q^b_{it}; Q^b_{it-1}) \\
\Pi^{a,b}_{it} &= [P^a(Q^a_t, Q^b_t) - c^a_t + \alpha_i g(r_{it})]Q^a_{it} + [P^b(Q^b_t, Q^a_t) - c^b_t + \alpha_i g(r_{it})]Q^b_{it} \\
&\quad - r_{it} - m(\Delta Q^a_{it}, \Delta Q^b_{it}; Q^a_{it-1}, Q^b_{it-1})
\end{aligned}$$

Lemma 2. *The Cournot game has an equilibrium which is unique.*

Proof. I will show that marginal profits are decreasing in all actions. It follows from Rosen (1965), as will be shown, that this result is sufficient for the existence

[4] m_- and m_+ are the two roots that solve the following equation for $\frac{\partial^2 m(\Delta Q^k_{it}; Q^k_{it-1})}{\partial Q^k_{it}\partial Q^l_{it}}$.

$$\begin{aligned}
&\left(\frac{\partial^2 P^l(Q^l_t, Q^k_t)}{\partial Q^l_{it}\partial Q^k_{it}} Q^l_{it} + \frac{\partial^2 P^k(Q^k_t, Q^l_t)}{\partial Q^k_{it}\partial Q^l_{it}} Q^k_{it} + \frac{\partial P^l(Q^l_t, Q^k_t)}{\partial Q^k_{it}} + \frac{\partial P^k(Q^k_t, Q^l_t)}{\partial Q^l_{it}} - \frac{\partial^2 m(\Delta Q^k_{it}; Q^k_{it-1})}{\partial Q^k_{it}\partial Q^l_{it}}\right)^2 \\
&\quad = \left(2\frac{\partial P^k(Q^k_t, Q^l_t)}{\partial Q^k_{it}} + \frac{\partial^2 P^k(Q^k_t, Q^l_t)}{\partial (Q^k_{it})^2} Q^k_{it} + \frac{\partial^2 P^l(Q^l_t, Q^k_t)}{\partial (Q^k_{it})^2} Q^l_{it} - \frac{\partial^2 m(\Delta Q^k_{it}; Q^k_{it-1})}{\partial (Q^k_{it})^2}\right) \\
&\qquad \left(2\frac{\partial P^l(Q^l_t, Q^k_t)}{\partial Q^l_{it}} + \frac{\partial^2 P^l(Q^l_t, Q^k_t)}{\partial (Q^l_{it})^2} Q^l_{it} + \frac{\partial^2 P^k(Q^k_t, Q^k_t)}{\partial (Q^l_{it})^2} Q^k_{it} - \frac{\partial^2 m(\Delta Q^l_{it}; Q^k_{it-1})}{\partial (Q^k_{it})^2}\right) \qquad (1.3)
\end{aligned}$$

This ensures that profits are strictly concave in quantities.

and uniqueness of equilibrium in the Cournot stage game. Let k, $l \in \{a, b\}$ and $k \neq l$. First and second order derivatives of the profit functions with respect to quantities are given by

$$\begin{aligned}
\frac{\partial \Pi^k_{it}}{\partial Q^k_{it}} &= P^k(Q^k_t, Q^l_t) + \frac{\partial P^k(Q^k_t, Q^l_t)}{\partial Q^k_{it}} Q^k_{it} - c^k_t + \alpha_i g(r^k_{it}) - \frac{\partial m(\Delta Q^k_{it}; Q^k_{it-1})}{\partial Q^k_{it}} \\
\frac{\partial \Pi^{k,l}_{it}}{\partial Q^k_{it}} &= P^k(Q^k_t, Q^l_t) + \frac{\partial P^k(Q^k_t, Q^l_t)}{\partial Q^k_{it}} Q^k_{it} - c^k_t + \alpha_i g(r_{it}) + \frac{\partial P^l(Q^k_t, Q^l_t)}{\partial Q^k_{it}} Q^l_{it} \\
&- \frac{\partial m(\Delta Q^k_{it}, \Delta Q^l_{it}; Q^k_{it-1}, Q^l_{it-1})}{\partial Q^k_{it}}
\end{aligned}$$

$$\frac{\partial^2 \Pi^k_{it}}{\partial (Q^k_{it})^2} = 2\frac{\partial P^k(Q^k_t, Q^l_t)}{\partial Q^k_{it}} + \frac{\partial^2 P^k(Q^k_t, Q^l_t)}{\partial (Q^k_{it})^2} Q^k_{it} - \frac{\partial^2 m(\Delta Q^k_{it}; Q^k_{it-1})}{\partial (Q^k_{it})^2} \tag{1.4}$$

$$\begin{aligned}
\frac{\partial^2 \Pi^{k,l}_{it}}{\partial (Q^k_{it})^2} &= 2\frac{\partial P^k(Q^k_t, Q^l_t)}{\partial Q^k_{it}} + \frac{\partial^2 P^k(Q^k_t, Q^l_t)}{\partial (Q^k_{it})^2} Q^k_{it} + \frac{\partial^2 P^l(Q^l_t, Q^k_t)}{\partial (Q^k_{it})^2} Q^l_{it} \\
&- \frac{\partial^2 m(\Delta Q^k_{it}, \Delta Q^l_{it}; Q^k_{it-1}, Q^l_{it-1})}{\partial (Q^k_{it})^2}
\end{aligned} \tag{1.5}$$

$$\begin{aligned}
\frac{\partial^2 \Pi^{k,l}_{it}}{\partial Q^k_{it} \partial Q^l_{it}} &= \frac{\partial^2 P^l(Q^l_t, Q^k_t)}{\partial Q^l_{it} \partial Q^k_{it}} Q^l_{it} + \frac{\partial^2 P^k(Q^k_t, Q^l_t)}{\partial Q^k_{it} \partial Q^l_{it}} Q^k_{it} + \frac{\partial P^l(Q^l_t, Q^k_t)}{\partial Q^k_{it}} + \frac{\partial P^k(Q^k_t, Q^l_t)}{\partial Q^l_{it}} \\
&- \frac{\partial^2 m(\Delta Q^k_{it}, \Delta Q^l_{it}; Q^k_{it-1}, Q^l_{it-1})}{\partial Q^k_{it} \partial Q^l_{it}}
\end{aligned} \tag{1.6}$$

For the results of Rosen (1965) to apply, the profit functions need to be concave. For firms that are active in one market only and therefore only take one action, this is equivalent to negative second order derivatives. As can be seen from Equation 1.4 this holds true as inverse demand is decreasing and concave and the costs of quantity adjustment is increasing and convex. For all firms that produce both products, the Hessian has to be negative definite. The Hessian is given by

$$H = \begin{bmatrix} \frac{\partial^2 \Pi^{k,l}_{it}}{\partial (Q^k_{it})^2} & \frac{\partial^2 \Pi^{k,l}_{it}}{\partial Q^k_{it} \partial Q^l_{it}} \\ \frac{\partial^2 \Pi^{l,k}_{it}}{\partial Q^l_{it} \partial Q^k_{it}} & \frac{\partial^2 \Pi^{l,k}_{it}}{\partial (Q^l_{it})^2} \end{bmatrix}$$

and its elements are given by Equations 1.5 and 1.6. Given that inverse demand for good k is decreasing and concave in the quantity supplied of good k, that inverse demand for good k is decreasing in the quantity supplied of good l as these are substitutes and the second derivative with regard to good l being nonpositive and the cost of quantity adjustment is increasing and convex and $\partial^2 m(\Delta Q^k_{it}, \Delta Q^l_{it}; Q^k_{it-1}, Q^l_{it-1} / \partial Q^k_{it} \partial Q^l_{it} \in (m_-, m_+)$, H is negative definite. Therefore, the Cournot stage game is a concave game and Theorem 1 in Rosen (1965) applies, i.e. an equilibrium point exists.

To show uniqueness of the equilibrium, it suffices to show that a weighted nonnegative sum of all players' payoff functions is diagonally strictly concave.

A sufficient condition for this to hold is that the matrix $[G(Q_t, r) + G'(Q_t, r)]$ be negative definite for some weights $r > 0$. $G(Q_t, r)$ is the Jacobian of the pseudogradient of the weighted sum of players' payoff functions and given by

$$G(Q_t, r) = \begin{bmatrix} r_1 \frac{\partial^2 \Pi_{1t}^k}{\partial (Q_{1t}^k)^2} & r_1 \frac{\partial^2 \Pi_{1t}^k}{\partial Q_{1t}^k \partial Q_{2t}^k} & \cdots & r_1 \frac{\partial^2 \Pi_{1t}^k}{\partial Q_{1t}^k \partial Q_{N_t t}^l} \\ r_2 \frac{\partial^2 \Pi_{2t}^{k,l}}{\partial Q_{2t}^k \partial Q_{1t}^k} & \cdots & \cdots & \vdots \\ \vdots & \cdots & \cdots & r_{N_t} \frac{\partial^2 \Pi_{N_t t}^{k,l}}{\partial (Q_{N_t t}^l)^2} \end{bmatrix} \tag{1.7}$$

where firms are ordered here from 1 to N_t such that those firms active in only one market come first and the firms active in both markets in the end. As can be seen from 1.7, $G(Q_t, r)$ is negative definite if marginal profits are decreasing in all actions. These marginal profits are given by Equations 1.4 to 1.6 and

$$\begin{aligned}
\frac{\partial^2 \Pi_{it}^k}{\partial Q_{it}^k \partial Q_{jt}^k} &= \frac{\partial P^k(Q_t^k, Q_t^l)}{\partial Q_{jt}^k} + \frac{\partial^2 P^k(Q_t^k, Q_t^l)}{\partial Q_{it}^k \partial Q_{jt}^k} Q_{it}^k \\
\frac{\partial^2 \Pi_{it}^k}{\partial Q_{it}^k \partial Q_{jt}^l} &= \frac{\partial P^k(Q_t^k, Q_t^l)}{\partial Q_{jt}^l} + \frac{\partial^2 P^k(Q_t^k, Q_t^l)}{\partial Q_{it}^k \partial Q_{jt}^l} Q_{it}^k \\
\frac{\partial^2 \Pi_{it}^{k,l}}{\partial Q_{it}^k \partial Q_{jt}^k} &= \frac{\partial P^k(Q_t^k, Q_t^l)}{\partial Q_{jt}^k} + \frac{\partial^2 P^k(Q_t^k, Q_t^l)}{\partial Q_{it}^k \partial Q_{jt}^k} Q_{it}^k + \frac{\partial^2 P^l(Q_t^l, Q_t^k)}{\partial Q_{it}^k \partial Q_{jt}^k} Q_{it}^l \\
\frac{\partial^2 \Pi_{it}^{k,l}}{\partial Q_{it}^k \partial Q_{jt}^l} &= \frac{\partial P^k(Q_t^k, Q_t^l)}{\partial Q_{jt}^l} + \frac{\partial^2 P^k(Q_t^k, Q_t^l)}{\partial Q_{it}^k \partial Q_{jt}^l} Q_{it}^k + \frac{\partial^2 P^l(Q_t^l, Q_t^k)}{\partial Q_{it}^k \partial Q_{jt}^l} Q_{it}^l
\end{aligned}$$

As these are all negative, $G(Q_t, r)$ is negative definite, which is sufficient for the equilibrium to be unique (see Theorem 2 in Rosen (1965).

□

The unique Nash equilibrium of the Cournot game solves the following set of equations

$$P^k(Q_t^k, Q_t^l) + \frac{\partial P^k(Q_t^k, Q_t^l)}{\partial Q_{it}^k} Q_{it}^k - c_t^k + \alpha_i g(r_{it}^k) = \frac{\partial m(\Delta Q_{it}^k; Q_{it-1}^k)}{\partial Q_{it}^k} \tag{1.8}$$

$$\begin{aligned} P^k(Q_t^k, Q_t^l) + \frac{\partial P^k(Q_t^k, Q_t^l)}{\partial Q_{jt}^k} Q_{jt}^k - c_t^k + \alpha_j g(r_{jt}) + \frac{\partial P^l(Q_t^l, Q_t^k)}{\partial Q_{jt}^k} Q_{jt}^l \\ = \frac{\partial m(\Delta Q_{jt}^k, \Delta Q_{jt}^l; Q_{jt-1}^k, Q_{jt-1}^l)}{\partial Q_{jt}^k} \end{aligned} \tag{1.9}$$

$$\begin{aligned} P^l(Q_t^l, Q_t^k) + \frac{\partial P^l(Q_t^l, Q_t^k)}{\partial Q_{jt}^l} Q_{jt}^l - c_t^l + \alpha_j g(r_{jt}) + \frac{\partial P^k(Q_t^k, Q_t^l)}{\partial Q_{jt}^l} Q_{jt}^k \\ = \frac{\partial m(\Delta Q_{jt}^k, \Delta Q_{jt}^l; Q_{jt-1}^k, Q_{jt-1}^l)}{\partial Q_{jt}^l} \end{aligned} \tag{1.10}$$

for all firms i that are active in market k and all firms j that are active in both markets, if these quantities are positive. Otherwise, i's equilibrium quantity is zero.

The optimal investment in R&D is determined taking into account the optimal quantity set in the successive stage and by the first order conditions of the profit function with respect to r_{it}, given by

$$\alpha_i g'(r_{it}^k) Q_{it}^k = 1 \tag{1.11}$$

$$\alpha_j g'(r_{jt})(Q_{jt}^k + Q_{jt}^l) = 1 \tag{1.12}$$

We are left with stage 1 of the game, the decision on whether to be active in a market and if so, in which one(s). An incumbent firm or a potential entrant will not be active at all if he cannot make positive profits in either market in isolation or in both markets in parallel, i.e. $\Pi^a(r_{it}^a, Q_{it}^a) \leq 0$ and $\Pi^b(r_{it}^b, Q_{it}^b) \leq 0$ and $\Pi_{it}^{a,b}(r_{it}, Q_{it}^a, Q_{it}^b) \leq 0$. A firm is active solely in market a if $\Pi^a(r_{it}^a, Q_{it}^a) > 0$ and $\Pi^a(r_{it}^a, Q_{it}^a) > \Pi^b(r_{it}^b, Q_{it}^b)$ and $\Pi^a(r_{it}^a, Q_{it}^a) > \Pi_{it}^{a,b}(r_{it}, Q_{it}^a, Q_{it}^b)$. Equivalently, a firm is solely active in market b if it makes positive profits in market b and these are larger than the profit from being only active in market a or being active in both markets. Lastly, a firm is active in both markets if it derives positive profits from its activity and if these are larger than if it were active in one of the markets in isolation.

Before analyzing how the presence of the second market affects firms from the first market, note that all firms that are active in market a in period $t-1$ could profitably be active in market b as well if they were solely active in market b.

Lemma 3. *Upon arrival of market b, $\Pi_{it}^b > 0$ for all firms i that are active in market a in $t-1$.*

Proof. As market b can profitably be entered by high and low type firms by assumption, $\Pi_{jt}^b > 0$ for all firms j that did not enter market a. Further, as investment in R&D is a perfect public input and innovations can be imitated one period after they arrived by firms in that market, a firm i that is active in market a has strictly larger margins and therefore strictly larger profits than a new entrant. □

Even though a firm can be profitable in market b in isolation, it might fail to profitably enter market b in addition to market a.

Lemma 4. *An incumbent from market a can be unable to profitably enter market b in addition due to a cannibalization effect or organizational diseconomies of scope.*

Proof. As both goods are substitutes $\partial P^k(Q_t^k, Q_t^l)/\partial Q_{it}^l < 0$, i.e. the price of one good is decreasing in the quantity of the other good. It can be seen from

Equations 1.9 and 1.10 that this reduces the optimal quantity of each good for a firm that is active in both markets. Suppose there are no organizational (dis)economies of scope, i.e. $m(\Delta Q_{it}^a, \Delta Q_{it}^b; Q_{it-1}^a, Q_{it-1}^b) = m(\Delta Q_{it}^a; Q_{it-1}^b) + m(\Delta Q_{it}^b; Q_{it-1}^b)$. Then the benefit of being active in both markets stems from the joint R&D program where every unit invested in R&D now reduces costs by $\alpha_i g'(r_{it})(Q_{it}^a + Q_{it}^b)$ whereas a unit invested in R&D by a firm which is solely active in one market reduces its costs by $\alpha_i g'(r_{it}^k)Q_{it}^k$. However, if this positive effect is outweighed by the cannibalization effect, the firm will prefer to be active in one market only.

Now suppose that the cannibalization effect and the joint R&D effect just cancel in a situation where there are no organizational (dis)economies of scope. As a result, the firm in question would be indifferent between being active in one or two markets. The presence of small diseconomies of scope, where $\partial m(\Delta Q_{it}^k, \Delta Q_{it}^l; Q_{it-1}^k, Q_{it-1}^l)/\partial Q_{it}^k \partial Q_{it}^l > 0$, is sufficient to make it unprofitable to enter the second market. This is due to the fact that both, optimal quantities as well as optimal R&D investments are reduced. □

Therefore, even though a firm could make profits in both markets in isolation, enjoys a technological advantage in market b due to its experience in market a and through the nature of R&D as a pure public input, it might still fail to profitably produce goods a and b simultaneously. This can end up being a threat for the very survival of the firm for two reasons. First, if it enters market b with a lower quantity than the high type entrants that are only active in market b, it is potentially subject to a future shakeout. Second, if the incumbent does not enter market b he could be forced to exit market a when market b grows large and ultimately replaces market a.

Proposition 2. *Although an incumbent firm survives a shakeout in the original market and has a technological advantage in the new market, it can fail irrespective of whether the firm enters market b or not.*

Proof. Lemma 4 shows that an incumbent from market a might not be able to profitably enter market b in addition. Suppose that the aggregate quantity in market b Q_t^b is strictly increasing. As $\partial P^a(Q_t^a, Q_t^b)/\partial Q_t^b < 0$ because goods a and b are substitutes, this creates a downward pressure on the price in market a. It follows from the optimality condition for the firm's quantity Equation 1.8 that this has a negative effect on the quantity supplied by the firms active in market a. As the price for good a is strictly decreasing in Q_t^b, there exists a $\bar{Q}_t^b$ for which $P^a(Q_t^a, Q_t^b) = 0$ and all firms exit market a, including the high type firms that entered market a in $t = 1$ and would therefore be certain to survive a shakeout.

Now suppose a high type firm that entered market a in $t = 1$ profitably enters market b upon occurrence but does so only with a small quantity $Q^b_{it} = \epsilon$ due to the cannibalization effect or organizational diseconomies of scope. That way it finds itself in a similarly disadvantageous position as low type firms or firms that enter later on and suffer from their lower quantities and therefore lower investment in R&D and consequently lower margins. This is because either its quantities for both goods are increasing but then the cannibalization effect or the organizational diseconomies of scope that made it optimal to enter market b only with a small quantity are still at work and will make growth in market b more costly than it would be were the firm active in market b in isolation. Or the firm is reducing the quantity supplied for one of its goods. While this reduces the cannibalization effect and the organizational diseconomies of scope, it reduces the optimal investment in R&D as well as it is increasing in the quantity supplied (see Equation 1.12). Either way, this firm will have lower margins in market b than a high type entrant that entered market b upon occurrence and is therefore more likely to exit market b when prices in market b decline. □

While the cannibalization effect can often be exogenous to the firms active in market a because the basic innovation comes form outside the industry, the organizational diseconomies of scope might be within the control of the firm. It is therefore of interest to better understand the empirical relevance of these two factors. While a full-fledged empirical analysis is beyond the scope of this paper, it might be useful to at least gain a better understanding of what could drive organizational diseconomies of scope and learn more about their relevance for the failure of firms. To this end, the next section studies three cases of firms that have been immensely successful for decades. Nevertheless, within a couple of years they lost their dominance and ultimately failed altogether. All three cases are characterized by the arrival of substitute products in combination with a technological advantage the incumbents had in supplying these products themselves. These cases therefore fit the framework used in the above model.

1.3 Case studies

1.3.1 Digital Equipment Corporation

> Why did an organization that was wildly successful for thirty-five years, filled with intelligent, articulate, powerful engineers and managers, fail ...? (Schein, DeLisi, Kampas, & Sonduck, 2004)

Digital Equipment Corporation (DEC) was a computer company founded in 1957. In 1987 it became the second largest computer manufacturer in the world.

DEC had reached $14 billion in sales, $1.3 billion in revenues and 120,000 employees by 1988 (Rifkin, 1993). DEC was known for innovations in many fields within the computer industry as well as for its leadership and culture. In 1986 its founder, Ken Olsen, was named "Entrepreneur of the Century" by Fortune Magazine, in 1988 Business Week called DEC the eighth most successful corporation in the US and Roberts (1991) called them "the most successful MIT spin-off company" (Schein et al., 2004). Not long after, though, the economic decline began and DEC reported a loss of $2.8 billion for its fiscal year 1992 (Rifkin, 1993). Only six years later, after laying-off thousands of employees and selling various business units, what remained of DEC was bought by Compaq. It took less than ten years for DEC to disappear after having introduced milestone innovations such as interactive computing, graphical user interfaces, operating systems technology, microprocessor design and networking to the computer industry within the preceding 35 years (Schein et al., 2004).

In 1957, Ken Olsen and Harlan Anderson founded DEC in an old mill in Maynard, Massachusetts. Already in their first year in business they made profits. At that stage DEC produced logic modules used for memory testing by the Bell Labs and Cal Tech. Two years later they developed their first computer, the refrigerator-sized Programmable Data Processor (PDP-1). After being in business for five years, DEC's profit grew to $807,000. A year later, in 1963, DEC introduced the first minicomputer, the PDP-5. In 1964, the PDP-6 was the first 36-bit computer and the PDP-8, sold from 1965, was the first mass-produced minicomputer. In 1967, sales hit $38 million, almost six times as much as in 1962. DEC also grew geographically by opening facilities in Canada, Europe, Australia and Japan. Five years later, in 1972, sales reached $188 million. This growth was sustained through the 80's until the collapse in the early 90's.

The foundation of DEC's tremendous success was the combination of "hiring the best and brightest from MIT and Lincoln Labs" (Schein et al., 2004, p. 136) and making good use of them in an industry that was just developing and in which there were no off-the-shelve solutions. Both factors shaped DEC as a company and were defining features for its culture that remained strong and largely unchanged until the very end. The need for inventions placed engineers at the center of the organization from the very beginning. The company's culture, strongly related to Ken Olsen's personal values, was combined with selective hiring and aimed at enabling engineers to provide the best solutions possible for any problem they encounter. Schein et al. (2004) describes this culture as consisting of five core genes and an additional five assumptions that are based on the first set but more market related. The first group consists of the belief that DEC can and will revolutionize computing and that the ultimate source of revolutionary ideas is the individual. However, it is recognized that the development of ideas has to be subject to intensive debate which will eventually lead to full utilization of the ideas potential. Schein et al. (2004) summarizes these two factors as “rugged individualism” and “truth trough conflict”. Further, Ken Olsen strongly believed in personal responsibility, i.e. those who come up with ideas or suggestions are the ones responsible for bringing the idea to fruition. The last of the five core traits of DEC’s culture was the sense of being a family from which no one can be rejected. Failure, therefore, was seen as a mismatch between a task and the employee rather than a failure of a DEC family member. Together, these core values created what appeared to DEC’s employees as a very strong and unique culture which they remembered as having been enormously empowering even years after DEC’s failure.

Based on these core values, DEC derived additional assumptions that did guide the conduct of the company and its employees. Based on the assumption that DEC can and will revolutionize computing and that it will ultimately find the truth through its internal processes, it was assumed that a good product will sell itself and that the judgment, of whether the product is good, can be made by its engineer. This was termed “engineering arrogance” by Schein et al. (2004). Although this might seem like a bad trait, the belief in and aiming for the ultimate truth in solving a problem also created a moral commitment to DEC’s customers: DEC saw itself committed to identifying and truly solving its customers problems. On its way to finding the solution, the company heavily relied on “the market as arbiter”, i.e. priorities in the developments of products were not assigned early on by management but left to the internal and external market to set. The last two fundamental characteristics, although seemingly contradictory, were defining for the way management worked at DEC. It was assumed that individuals can and will successfully work together and coordinate their activities in the interest of the company. At the same time, though, DEC’s founder and CEO until 1992, Ken Olsen, kept a special position within DEC in which he retained power no one else had in DEC.

DEC’s culture of empowerment, shaped by excellent engineers, is seen as the source to its milestone innovations such as PDP and VAX. However, it also is the key for understanding its failure. The combination of economic success, vastly talented engineers , empowerment in the sense that good ideas, good product design had to be pursued and prioritizing was delegated to the market, caused troubles as the computer industry matured and markets for standardized products, in particular the IBM PC, arose.

Although it is often said that Digital failed to enter the market for PCs, this perspective is not quite correct. In fact, they introduced three different PCs to the market at the same time: Rainbow, DECmate and Professional 350. Each running a different operating system. What they failed in was to introduce an IBM compatible PC, the then standard in the industry. DEC's sales of other products did not manage to keep the company afloat as the PC revolution unfold. Especially Digital's original market of minicomputers started to become obsolete in the early 90's when microprocessors became more powerful[5].

In providing own products to the starting PC market, Digital acted according to the values that made it a large and successful company. They developed the products in-house, with the skilled engineers that will find the right solution eventually and did leave prioritizing between Rainbow, DECmate and Professional 350 to the market. However, the market opted for the IBM PC that arrived on the market two years before DEC's PCs because IBM made use of OEM suppliers for several parts of its system which sped up development and production considerably. Finally, Digital could have entered the market for IBM compatible PCs just like DELL and HP did, however, this fundamentally conflicted with DEC's "engineering arrogance". As Ken Olsen put it: "we do not copy!"

1.3.2 Metro-Goldwyn-Mayer

> For audiences at home and abroad, MGM was Hollywood at its most Hollywood in the best sense of the word, proved by the fact that MGM grosses were reliably leagues ahead of its competitors' and had been since the company was formed in 1924. (Eyman, 2008, p. 3)

20 years after Metro-Goldwyn-Mayer (MGM) was founded, its studios covered 167 acres (about 67 ha), employeed 6000 people, owned 40 cameras, 60 sound machines and had 33 actors as official stars as well as 72 featured players and 26 directors under contract (Eyman, 2008). In the fiscal year 1944-45 MGM's profit was $22.4 million. In contrast, Paramount made $14.5 million, Fox made $10.9 million and Universal had profits of $3.4 million. "Within the industry, when Paramount or RKO made a particularly good picture, it would be said "it was of MGM quality"; at a sneak preview, when the MGM logo of a roaring lion appeared, there would be a spontaneous burst of applause from the audience" (Eyman, 2008, p. 3).

MGM's fall began in the 40's. In 1949, they still had a 22% market share, the same as in 1939. Until 1956, MGM's market share dropped to 17% and 1957 saw a $7.8 million loss from motion pictures. A little more than ten years later, at a net loss of $35.366 million, MGM was bought by investor Kirk Kerkorian and most of MGM's assets were sold.

[5]A development for which DEC provided key solutions with its Alpha-series.

Although MGM was formed of Metro Pictures, Goldwyn Company and Mayer Productions, Louis B. Mayer was the driving force of what would become MGM. And MGM became "different". While other studios, such as Paramount, went into assembly line production of B movies to fill the theaters of their owners, MGM went after the growing middle class to entertain them with classy films. For Mayer, movies had to be an escape from reality, a dreamworld, beautiful and luxurious. And he was willing to spent the money necessary to achieve this goal. In this spirit he telegraphed to a director "Spare nothing, neither expense, time, nor effort. Results only are what I am after." (Eyman, 2008, p. 111). Similarly, Mayer had parts of "The Big Parade" reshot after the film was finished increasing the cost from $250,000 to $382,000. "The Big Parade" became one of the biggest successes of the silent film era and grossed $6 million, a third of the industry's earnings in 1925. With the additional success-stories of "Ben Hur" and "The Merry Widow" MGM made a profit of $4.7 million in its first year. It came as close as $1 million to Paramount that had taken 10 years to build up such a production.

MGM had developed a system that was able to produce A movies almost as on assembly lines. Actor Ricardo Montalban described it as: "MGM functioned like General Motors. It was run with such efficiency that it was a marvel. It was done by teamwork; they could project the product, and the product was not any individual movie, it was the actor. They created a persona that they thought the public would like; they tailor-made the publicity to create a persona through-out the world. It was amazing." (Eyman, 2008, p. 4). In this quote Montalban describes what is a lasting part of MGM's legacy: the perfection of creating stars. Mayer had a sense for faces that people liked and he did what was necessary do bring them under contract for MGM. When Mayer saw Greta Garbo for the first time in Berlin, his daughter Irene remembered him to be "hell-bent". "He said it had nothing to do with beauty, "It's what she conveys and the expression emanating from her eyes". He wanted to meet her that day, and a meeting was arranged...". Thereafter, Greta Garbo came under contract at MGM and a Hollywood-legend.

Mayer and his head of production, Thalberg, built MGM around their stars. They would "establish an MGM star with a spectacular picture – John Gilbert in "The Big Parade", Ramon Navarro in "Ben-Hur" – then put him in three or four medium-budget vehicles for every high-budget picture." (Eyman, 2008, p 118). Similarly to their roster of stars, MGM had numerous producers and directors under contract, binding the biggest talents of the industry to MGM. Mayer himself described his plans as follows: "I'm going to build up the biggest collection of talent so that this studio can't fail. ... If you come across any actor, director or writer who looks promising, let me know and I'll sign'em up."

(Eyman, 2008, p. 154).

Apart from its stars and talent, MGM stood out through the aesthetics its pictures showed. During the silent film era, MGM pictures were "often knock out combinations of lush art direction and spectacular camera work bespeaking a radiant self-confidence...[and]... romantic photography" (Eyman, 2008, p. 120). And even for the pictures that weren't one of the big spectacles, "MGM offered a little something extra".

The combination of these aesthetics, Mayer's sense for stars and talent and his drive to bring these factors together to build a viable business reflected the values he stood for. As Mayer's biographer puts it: "The movies weren't just a business for Mayer, they were vehicles for the projection of his own fantasies of social mobility and sexual attractiveness. He took the fantasies seriously, he took the audience seriously, and the took the movies seriously." (Eyman, 2008, p. 149).

However, as defining as these aesthetics were for MGM's leading position in Hollywood, they were also a major cause for its fall. When the audience's tastes began to shift away from MGM's beauty and luxury, the studio failed to follow suit. It was seen as just wrong. In 1945, when watching a close-up scene of Audrey Trotter in "Lady in the Lake", Mayer would ask the director: "Why does her hair look awful?". After it was explained that she just got up in the middle of the night, Mayer replied: "I don't care if she's coming out of the toilet, her hair can't look like that." (Eyman, 2008, p. 380). In the same vein, Mayer disliked King Vidor's "The Crowd" because of one scene were a toilet was shown in a bathroom. He acknowledged that "We all have our natural functions, but we don't put them on the screen." (Eyman, 2008, p. 403). The drifting apart of opinions on what a movie could or could not show was clearly realized. It didn't change the policy of MGM, though, but left them frantic. After Mayer had seen Billy Wilder's "Sunset Boulevard" in 1949, he said: "I don't know what it is, the picture business. Everyone wants to see this," accompanied by a clutch at his crotch. "Men with dirty faces, women with messed-up hair. Who wants to look at garbage? We always forget what we're doing! We're making moving pictures! They have to be beautiful! Every frame has to be beautiful!" (Eyman, 2008, p. 432).

Besides the change in tastes that MGM did not follow, there was a new medium on the rise: television. And with the growth of television, cinema fell. Between 1946 and 1948, movie attendance fell from 80 million per week to 67 million while ownership of TV-sets grew from 136,000 in 1947 to 700,000 in 1948 and reached 10 million in 1951. During that time, 6,500 movie theaters closed within a three-year period. Instead of using its position in moving pictures to shape TV, MGM did nothing. As screenwriter Millard Kaufman remembers:

"The studio had a preoccupation with its primary place in the picture business, so it was the last studio in the world to accept TV and turn out TV product. The whole company thought TV was nothing but midgets in a fishbowl, and they were wrong. There was a time when everybody wanted to be with MGM, but with television nobody wanted to be with MGM. So everybody got away hell ahead of them, and then they got frantic." (Eyman, 2008, p. 463).

With its failure to acknowledge and follow the changing taste of its audience and the rise of television, MGM, the then industries greatest, lost market share, profits and its position as defining studio in Hollywood. Although it did survive that way till it was bought by Kirk Kerkorian in 1969, the studio that was MGM in the 20's, 30's and 40's was gone. Finally, in 2010 MGM went bankrupt and filed for Chapter 11.

1.3.3 Kodak

> We were ahead of the curve in digital even though we were pretty much a film and chemical company. We did a lot of research in digital because we knew at some point in time the world would change. We invented the digital camera. So, being the first ones there we continuously worked in the labs so to make sure when that change was made we were prepared for it. (Paul Porter, Kodak's Director of Design and Usability in Lucas Jr & Goh, 2009)

George Eastman began to manufacture dry plates in 1880 and invented roll film in 1885 which was used in the first Kodak camera introduced in 1888. In the following decades, Kodak produced a range of folding and pocket cameras that simplified the process of photography and opened it to the masses. In 1934, Kodak had introduced the first Retina camera. These were produced in Stuttgart, Germany, and, as Kodak's traditional top-line 35mm camera for advanced amateurs, were highly sought after (Snyder, 2013). In 1935 Kodak introduced Kodachrome, the first subtractive color film. It was produced for 74 years until 2009 and became very much appreciated by professionals and amateur photographers. Magnum photographer Steve McCurry described it as "You just look at it and think, this is better than life" (Dobbin, 2008). A quote that is illustrated by the fact that McCurry's legendary National Geographics cover photo the Afghan girl was shot on Kodachrome. Kodak's high quality products enabled it to capture most of the US market for photography with a 90% market share for film and 80% for cameras in 1976 and supported a growth in earnings from $1 billion in 1962 to $10 billion in 1981 (Lucas Jr & Goh, 2009). Kodak Eastman was not only a dominant company in photography, though. For decades, it was among the most successful US firms; it was added to the Dow

Jones Industrial Average in 1930 and joined the S&P500 and the Fortune 500 upon their creation in 1957 and 1955. In addition, it was rated among the world's five most valuable brands until the 1990's (Economist, 2012).

During the 1990's and 2000's photography became digital and with it came Kodak's decline and death. Even though an engineer at Kodak invented the first digital imaging sensor in 1976 and Kodak was the first to produce a megapixel sensor, good enough to produce prints, Kodak filed for Chapter 11 in 2012 only little more than a decade after its profits peaked at $2.5 billion in 1999.

As Paul Porter is quoted in the beginning of this section, Kodak was a film and chemicals company. For most of its life, Kodak was known for both its innovations to make photography easier for the masses as well as provide high quality. Synonymous with the former fact is the well known Kodak slogan "You press the button, we do the rest.", which accompanied the company from the very beginning. Synonymous for the latter are endorsement as the one by Steve McCurry and other professional photographers who built their career on the quality of Kodak's products and services. However, if Kodak would have solely been a chemicals and film company, its demise might seem less puzzling. But that was not the case. In contrast, it was Kodak who pioneered digital photography but failed to generate profits from these innovations apart from royalties and licensing fees that would make up big parts of Kodaks earning in its final years. It might seem the more surprising that Kodak failed the transition to digital when realizing that at least from the early 90's that transition had become a clear focus of top management. To facilitate this change, George Fisher, a former CEO of Motorola became CEO at Kodak in 1993. And it wasn't for a lack of trying that they finally did not succeed. In fact, Kodak introduced more than 50 products related to digital photography, among them not only digital cameras but also photo cds and software to share ones photos with others online. Further, at one time Kodak had 23 scanner projects running in parallel (Lucas Jr & Goh, 2009).

Therefore, the failure to make the transition to digital imaging does not seem to be due to a lack of skill or technology nor was it that digital photography was not on the CEO's agenda[6]. It was more that Kodak's culture was one of being a chemicals and film company and going digital confronted both many employees and lower level managers with a future that conflicted with what they new of the technical side of photography as well as the way of doing business[7]. Lucas Jr and Goh (2009) cite George Fisher in an interview looking back at his time as CEO saying: "I think that the fear drove paralysis that manifested

[6]Although it can be said that the growth of digital photography was underestimated.

[7]Kodak's business during the film era was very much one of the "razor-blade" type, i.e. they sold cameras but made their money with film, paper and services.

itself as time went on, to rigidity with respect to changing our strategy and I didn't see that at the start...we really had to work very aggressively to get middle management first of all understanding what we were trying to do and believe that this was a story of opportunity, that we were in the picture business, that digital was just a technology just like film was, and that picture business opportunity was gigantic, and there was a future for them...Their arguments would be all over the map...Kodak can't succeed in this market. We've tried some consumer products before and failed miserably. There is no money in this business; it's all low margin...There is a new set of competitors...we don't know anything about them. I also believe firmly...(that) digital imaging was everything in the future. Therefore we were either going to be in the picture space...or we weren't. If we were going to be in it, we'd have to make an all out assault on digital imaging which meant a step function change."

In that way, Kodak started the industry of digital photography by making the essential inventions. However, its organization was built around film-based photography that was very successful for more than 100 years but the benefits were largely reaped by its competitors, especially Japanese electronics companies such as Sony, Canon or Nikon. The combination of the declining market for film and Kodak's failure to make profits with its digital business lead to the fall that culminated in Kodak's filing for Chapter 11 in 2012, 132 years after George Eastman started his business.

1.3.4 Comparison

The cases of DEC, MGM and Kodak differ widely. MGM started to fall even before DEC was founded. So, failure of firms does not seem to be limited to the technological revolution that DEC and Kodak faced in the 90's and 2000's. Kodak, in turn, was already a behemoth when MGM and DEC peaked and ultimately died after 132 years apparently ruling out a naturally limited lifetime of firms of just a few decades. Then, MGM differs from DEC and Kodak in that is was not a manufacturing firm in high tech industries. This seems to suggest that maybe no company, however successful at some point in time, is guaranteed to survive. Also, the way these three firms failed differ. While it is often assumed that large and old firms are too slow to adapt to new technology, this is not necessarily the case. Kodak invented the very technology that ultimately caused its failure and DEC entered the PC market that would push its minicomputer business to extinction. MGM, though, can be thought of being too hesitant to enter the television industry.

However, all three cases feature parallels as well. First of all, DEC, MGM and Kodak had been immensely successful in their market not only in the sense that they had been technologically superior to their competitors but also were highly profitable. Change as well was an inherent part of these firms' development. DEC introduced interactive computing and graphical user interfaces to the industry. MGM went from silent black & white pictures to sound and color and musicals. Kodak joined the market for 35mm cameras and different kinds of film such as the K-14 Kodachrome.

1.4 Discussion

In the following, I want to discuss three aspects of the preceding analysis. First, Klepper (2002) represents one class of models that aims at analyzing the evolution of industries. Therefore, I will discuss whether a similar extension as suggested above could incorporate the pattern of failing previously successful firms in other models of industry evolution. Second, the above model identified a cannibalization effect as well as organizational diseconomies of scope as potential factors for firm failure. Based on the three case studies, I will discuss the role these two factors played in the failure of DEC, MGM and Kodak. Third, the model is silent about the cause for organizational diseconomies of scope. I therefore want to discuss the observations from the case studies in light of existing theories and identify open questions for future research.

Closest to the model of Klepper (2002) is probably the learning by doing model of Dasgupta and Stiglitz (1988). In their paper, a firm's cost in a later period is decreasing in the output produced in an earlier period. Based on learning-by-doing and firm heterogeneity, Dasgupta and Stiglitz (1988) show how an initial cost advantage for a firm can accumulate over time and contribute to increased market concentration. This result is qualitatively similar to the one derived from the model in Section 1.2.1. Accordingly, it would also appear as a puzzle how one of the Dasgupta and Stiglitz (1988) type firms with initial cost advantage become disadvantaged in a market that uses the same technology. In terms of the above case studies, with learning-by-doing type firms, it is not obvious why MGM did not use their production technology from the movies (where they had acquired an advantageous position) to produce material for TV. Similarly, DEC as the leading manufacturer of minicomputers could have used their know-how and leading position in the industry to supply IBM compatible PCs under their own name. However, they chose not to. And even though digital imaging requires a different technology from the traditional film-based photography, Kodak can be thought of as having been in an early and advantageous position in that market. Kodak was not only the firm inventing and producing the first digital camera and the first megapixel camera for a price below $1000, it held essential patents in digital imaging (which towards the end of its life would become its most important source of income). Therefore, also a Dasgupta and Stiglitz (1988) type model would require an extension that incorporates organizational diseconomies of scope to explain the observed pattern.

In Jovanovic (1982) an industry is modeled in which firms can have high or low costs but are only imperfectly informed about their type. Over time, when these firms receive signals about their type, expected future profits are adjusted and firms that receive sufficiently unfavorable signals leave the market. Similar to the cases before, it is not apparent why firms that learned that they are of the low cost type would either not enter the new market which requires the same technology or fail to be profitable in this market.

Jovanovic and MacDonald (1994) study the evolution of an industry where the market starts to exist with a basic invention that will be refined by some firms which are then high technology firms (as compared to those firms that use only the basic invention and are called low technology firms). Taking the model at face value, the invention of the TV and the IBM PC could be seen as basic inventions for which MGM and DEC happened not to develop the refinement. However, this would raise the question whether it is a reasonable assumption to assume that those refinements are delivered randomly when those firms used an essentially identical technology for decades.

It therefore appears to me that the immense success of firms in one market and the rapid failure of those firms in a market where they have a technological advantage is not easily explained by other models of industry evolution either. In that way, the above analysis is not necessarily particular to Klepper (2002) type models.

To arrive at a better understanding of the relative importance of the cannibalization effect and organizational diseconomies of scope, consider the starting quote for the Kodak case study. Apparently, Kodak was eager to enter the new market. So, strategic considerations of protecting their original business by being absent from digital imaging did not seem to drive decisions at Kodak. This logic is supported by George Fisher's view that digital imaging will be the future and that Kodak would need to embrace it if it wants to continue being a player in imaging. Further, it seems that cannibalization was not the driving force of DEC's decision not to enter the market for IBM compatible PCs. While the cannibalization effect could have, in principle, been based on the competition an IBM compatible PC would have created towards both, their minicomputers and their own PCs, I am convinced of neither. Apparently, DEC did not worry to a great extend about PCs cannibalizing their minicomputers otherwise they would not have introduced three different models themselves. In addition, as all three PCs they offered were based on different systems, the existence of a close substitute in the own product range did not seem to impede the willingness to bring a new product to the market. This strategy is consistent with the observation in Schein et al. (2004) that prioritization was delegated to market processes. In the case of MGM, the case study suggests that its CEO perceived TV as inferior to cinema and therefore did not produce for TV. The cannibalization effect, however, requires that the products in question are close enough substitutes. While they might have been in reality, at MGM they "thought TV was nothing but midgets in a fishbowl" (Eyman, 2008, p. 463). In that way, MGM's decision not to enter TV is not consistent with a cannibalization effect.

The case studies reveal that the three firms dealt quite differently with the emerging new markets. While Kodak created the new market, tried to shape it from the very beginning and its top management aimed at making Kodak the dominant player in digital imaging, DEC and MGM can be seen as having been far more hesitant to embrace the new developments. However, also the cases of MGM and DEC differ considerably. While it seems that neither DEC's founder and CEO, Ken Olsen, nor DEC's engineers were willing to adopt the standard of the IBM PC, Mayer's hesitance to follow the new tastes of movie-goers and TV was met by many talents leaving MGM as they realized that ignoring this change did not promise a bright future. It might therefore not be surprising that there is no unified theory that can explain the observed organizational diseconomies of scope. Nevertheless, I belief that certain models can shed light on factors contributing to organizational diseconomies of scope.

Cyert and Kumar (1996) show how agency costs can increase the cost of technology adoption even if the technology itself is present in the firm. This is based on the argument that individuals who have the necessary knowledge have an incentive to cash-in on that information asymmetry. As a consequence, "these adaptation costs are shown to imply that such firms have higher effective learning or information search costs than smaller firms that may be potential entrants" (Cyert and Kumar (1996)). Another way in which agency costs can increase the costs of organizational change is presented by Schaefer (1998). In his model, he analyzes a situation in which agents that expect change can divide their effort between productive actions and influence activity aimed at affecting the direction of change for personal benefit. Analyzing a setting of bounded rationality, Hirshleifer and Welch (2002) present a model of memory loss in which past actions are better remembered than past information. In their model, new projects arrive which can either be good or bad and the firm has the option to either adopt or rejected those projects. The authors show that compared to a situation without memory loss, a stable environment leads to a situation in which a firm continues to follow old policies.

In contrast to the previous models, where situations were analyzed in which an additional activity or change in general leads to higher costs, Carrillo and Gromb (1999) show how inertia can be a profitable and a deliberate choice of a firm. In their model, agents can invest in culture specific capital and the principal can decide to adopt a new culture. However, the principal might find it optimal to commit to cultural inertia so as to protect the culture specific capital of his agents and therefore provide incentives to invest in the first place.

In a growing industry such as computers in the 80s and 90s, an organization like DEC that aims at resolving conflict through discussion and not based on power, there is wide scope for costly influence activity as in the model of Schaefer (1998). Also, in an organization such as Kodak, where resources had to be shifted from the traditional film based business to digital imaging it is conceivable that different business units used their knowledge to extract rents such as suggested by Cyert and Kumar (1996). However, while the above models on agency problems can explain why it might be more costly for a firm to join a new market in case it is already active in another market, these cannot explain why such firms fail. All models crucially depend on the assumption that there are rents that can be extracted by agents due to asymmetric information. Therefore, a firm should not fail due to rent extraction by its agents if they attach reasonable weights on future income from these organizations. In addition, while an organization in Carrillo and Gromb (1999) might end up with an unprofitable culture after a change in the environment occurred, it is not apparent why there would be opposing movements within an organization as observed in Kodak where top management pushed the shift to digital for years whereas lower levels of the hierarchy seemed to resist the change.

Further, the case studies suggest that some individuals within the organization were just not willing to change just as if the business model was part of their preferences. The focus of Mr Mayer on beautiful and luxurious movies and the dedication of Ken Olsen and DEC's engineers to providing in-house solutions for their customers are examples. It appears to me as an interesting line of future research to investigate what drives these individuals' reluctance to change in the presence of large monetary losses that are associated with sticking to the old business model.

1.5 Conclusion

In the above I aimed at resolving the puzzle that evolution of industry models make good predictions as to which firms are likely to succeed in a market but fail to explain why these firms fail nevertheless upon the emergence of additional markets that use the same technology. I identify two effects that can cause failure for formerly large and successful firms in markets where they have a technological advantage: a cannibalization effect and organizational diseconomies of scope.

By conducting case studies of former industry leaders Kodak, DEC and MGM I show that organizational diseconomies of scope were the prime reason for failure by making it prohibitively costly even for a technologically superior firm to enter a new market or operate profitably in the new market.

Chapter 2

Emotions and Effort*

2.1 Introduction

This paper addresses the question of how employees' effort provision reacts to a change in the work environment. When markets are subjects to change through entry and exit, innovation or the arrival of new markets, a change in firms strategy is called for. Often, these strategy changes require a change in the employees' work environment as colleagues might get laid off, new ones get hired, and resources are reallocated. It could be expected that, as a consequence, some people gain while others lose. However, some policies seem to be more accepted than others. It is, for example, very unpopular to cut employees' wages. In contrast, working longer hours for the same wage seems to be more acceptable. Under such circumstances, a firm that is trying to increase efficiency might rather increase working hours and keep wages constant than reduce wages at constant hours.

The relationship between wages and effort has already received scrutiny from economists. In particular, Akerlof and Yellen (1990) formulated the fair wage-effort hypothesis and studied its consequences. The fair wage-effort hypothesis is based on empirical results from psychologists (see e.g. Lawler & O'gara, 1967; Valenzi & Andrews, 1971; Pritchard, Dunnette, & Gorgenson, 1972) that report reduced effort or even left jobs as a result of wage decreases and states that a unit of effective effort exerted by employees will equal the ratio of perceived remuneration to the perceived value of that unit of effective effort.

The fair wage-effort hypothesis received additional support from laboratory

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experiments. Gächter and Thöni (2010) show that subjects in a three person gift-exchange game respond negatively to disadvantageous wage discrimination. Nosenzo (2013) and Greiner, Ockenfels, and Werner (2011) support the view that social comparison is a key factor in driving a negative response, while a wage cut in itself might not be sufficient[2]. Nevertheless, Falk, Fehr, and Zehnder (2006) show that the introduction of a minimum wage is sufficient to increase the reservation wage of participants in an experiment without social comparison. Therefore, there is evidence from laboratory experiments supporting the hypothesis that unfair treatment of workers results in withdrawal of effort. However, it is less clear what exactly is perceived as unfair; it might even be equal pay (see Abeler, Altmann, Kube, & Wibral, 2010)[3]. Further, the evidence on the effect of preferential treatment of workers is less clear.

In field experiments, workers react in different ways to unfair treatment. While Cohn, Fehr, Herrmann, and Schneider (2014) show how wage cuts and social comparison for disadvantaged workers reduce effort, Hennig-Schmidt, Sadrieh, and Rockenbach (2010) demonstrate invariance of work effort to positive and negative wage comparison. In between those two findings, Lee and Rupp (2007) report some negative effect of wage cuts that are short-lived and Kube, Maréchal, and Puppe (2013) report negative effects of wage cuts on productivity but no effect of wage increases[4].

Outside the field of economics, several studies were concerned with fairness and counterproductive work behavior (see e.g. Spector, 1978), employee theft (see e.g. Greenberg, 1990, 2002) and legal claims of former employees (see e.g. Goldman, 2003). However, at the same time, employees can exhibit organizational citizenship, i.e. behavior that is to the advantage of a firm or organization in general (see e.g. Spector & Fox, 2002, 2010).

Therefore, employees can exhibit desirable as well as undesirable behavior depending on how they feel treated. Based on that, it will be in every organization's interest to correctly foresee the effect a policy change will bring about. However, organizations often will, ex ante, not have the knowledge necessary to make adequate predictions as this requires knowing what employees deem fair, whom they compare themselves to and how they judge their current situation.

[2]Not all information seems to be detrimental to the disadvantaged workers, though, as Azmat and Iriberri (2016) show in studying the effect of relative performance feedback in a real effort experiment with piece rate payment. Here, the performance feedback increases performance for all workers potentially because differences in payoff are based on subjects actions and not due to differences in the wage.

[3]Abeler et al. (2010) study a gift exchange game where two agents chose effort and a principle choses wages. The authors observe lower effort in the treatment where the principal is restricted to pay both agents the same wage. In contrast, effort levels are high when the principle can pay the agents different wages.

[4]Cohn, Fehr, and Goette (2014) show that the lack of an effect of wage increases can be explained by the fact that only those employees increase their effort who felt underpaid before.

Because of that, possessing an indicator as to how employees will react would prove useful.

We propose one such indicator, namely the facial expression of emotions, and study its role in the context of changing work environments. The facial expression of emotion is particularly suited as an indicator as they occur universally in emotionally arousing situations, are linked with subjective experience, are judged universally and discretely and have important social functions (Matsumoto, Keltner, Shiota, OSullivan, & Frank, 2008). We conduct real effort experiments that are characterized by the disadvantageous treatment of some individuals while others receive a preferential treatment. To address the question of how to promote efficiency, we compare both changes in wages and changes in work load. At the same time, we employ facial expression analysis using the software Facereader to track subjects' emotions during the experiment and conduct the questionnaire STAXI-2 (Rohrmann, Hodapp, Schnell, Tibubos, & Schwenkmezger, 2013) to receive additional information on how subjects deal with emotions[5].

In the remainder of the paper, Section 2.2 provides an introduction to the concept of emotions and Section 2.3 describes the experiment. In Section 2.4.1 I report descriptive results of effort and the facial expression of emotion before turning regression analysis in Section 2.4.2. I discuss the results in Section 2.5 and Section 2.6 concludes.

2.2 Emotions

> The study of expression is difficult, owing to the movements being often extremely slight, and of a fleeting nature. (Darwin (1872), p. 13)

Conducting experiments enables researchers to identify causal effects and, by having done so, gain insight of cause and effect of human action and interaction. Outside the laboratory, however, conducting experiments might not always be possible. Still, people have an interest in foreseeing the effect a change, for example in the work environment, will have on individuals. This way, policies could be adapted if need be. The question remains, though, how one could reliably tell that this need arises.

While an easy way of approaching this problem would be to just ask the people affected, this comes with potential problems. One being that people might not be willing to reveal their true interest and opinion for fear of retaliation.

[5]Some previous literature has already described the mediating role of emotion in behavior in the work context (see e.g. Fox & Spector, 1999; Fox, Spector, & Miles, 2001).

Another reason might be that useful feedback would require the individuals affected to anticipate how they will, in the future, react to the policy change.

Besides verbal expression, people express themselves in non-verbal ways, in part by means of facial expression. To be useful to researchers, there should be some generality of human facial expression and a theory of what these are. Both components apply to emotions, which makes it an interesting concept to study within economic experiments. Indeed, the empirical regularities associated with emotion have been termed "laws of emotion" (see Frijda, 1988).

Before we go on, it will be useful to define emotion. While everyone has an intuitive understanding of what emotion is or means, there has hardly been a consensus in the sciences as to what emotions are. Scherer (2005) for example defines emotion as "an episode of interrelated, synchronized changes in the states of all or most of the five organismic subsystems in response to the evaluation of an external or internal stimulus event as relevant to major concerns of the organism". Therefore, the experience of emotion has a start, which is a trigger that can be either external or internal, and has an end. In between, several components of the nervous system are employed to respond to the trigger through physiological changes. In addition, for emotions to be triggered it is necessary that the stimulus is perceived as important to the individual.

Based on the above definition, the facial expression of emotion is just one component of an emotion but it is an element of emotion that is particularly suit to be studied within economic experiments. One reason being that it is easily accessible through video footage of participants without interfering with the actual experiment in the same way fMRI scans would. In addition, facial expression analysis is much more economical, permitting larger sample sizes or a larger number of tests. At the same time, the analysis of facial expression might not suffer more from willful moderation by experimental subjects than fMRI scans. Therefore, the above cited "laws of emotion" can be expected to apply to the facial expression of emotions in the laboratory as well.

The idea of facial expression of discrete emotion being universal to all humans goes back at least to Darwin (1872) but has received renewed attention among psychologist following the work of Ekman (1970) and Izard (1971). As Darwin before, Ekman (1970)'s results were based on empirical work, where people were shown pictures of facial expressions and interpreted these with a high level of consistency. In his study, Ekman (1970) was able to show that not only within one culture but also across cultures this interpretation of facial expressions was highly consistent[6]. In subsequent research, at least 27 studies have replicated these early results on the universal recognition of the facial ex-

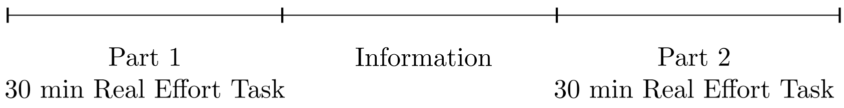
[6]To arrive at this conclusion, he worked with people from the Southeast Highlands of New Guinea, which, at the time of his research, had not been exposed to western culture.

pression of emotion (see e.g. Matsumoto, 2001; Matsumoto et al., 2008). The basis for the universal recognition can be found in the universal expression of emotion. On the lowest level, this requires that faces have the same anatomy so as to being able to employ facial muscles for the expression of emotion which is indeed the case (Gray, 1966). Already Darwin (1872) showed that different emotions show distinct patterns of movement of facial elements. Sadness according to his studies is expressed by depressed corners of the mouth and raised inner corners of the eyebrows whereas surprise is described as consisting of raised eyebrows, open mouth, open eyes and protruding lips (Matsumoto et al., 2008). Based on those common movements as part of the facial expression of emotion, Ekman and Friesen (1978) developed the Facial Action Coding System (FACS) which categorizes one or more muscles into Action Units (AUs). Therefore, the facial expression of emotions can be summarized by their AUs. A comparison of Darwin (1872)'s description of the expression of emotion reveals a close correspondence to the classification based on the FACS (Matsumoto et al., 2008). In addition to the universal expression and recognition of emotion, previous research has also shown that the facial expression of emotions correlates with subjective experience of emotions (see Matsumoto et al. (2008) for a summary).

Despite its prominence in psychology research and every day life, emotion research is still in its infancy in the field of economics. Nevertheless, there has been some theoretical as well as empirical work. In particular, Elster (1996) discusses in how far the concept of emotion fits into the rationality approach of economics and Elster (1998) shows how emotions affect behavior. In addition, Loewenstein (2000) and Rick and Loewenstein (2008) study how emotions could be incorporated into the economists' utility framework. In economic experiments, researchers studied the effect of emotions on behavior by inducing certain emotions. In that line of research, Andrade and Ariely (2009) have found that in ultimatum games, happy responders are less likely to reject unfair offers than those subjects that were induced as being angry. In addition, Lerner, Small, and Loewenstein (2004) induce disgust and sadness and show how this treatment result in subtle differences in subjects' endowment effect. In a different line of research, emotions were not induced through videos or pictures but resulted more directly from the experimental design. Here, Nguyen and Noussair (2014) report a relationship between risk aversion and emotion with a more positive emotional state correlating with more risk taking. Habetinova and Noussair (2015) study charitable giving and emotions and find that the decision to donate is independent of prior emotional state but valence decreases after a donation[7]. What is more, van Leeuwen et al. (2016) provide evidence

[7]The decrease in valence is measured by the software Facereader. In self-reports, subjects

Figure 2.1: Structure of the Experiment



for the reliability and information content of facial expressions by showing that participants in an experiment can predict rejections in ultimatum game based on picture of responders at rates better than chance.

2.3 Experiment

The experiments were conducted in July and August 2015 as well as in January and February 2016 in the experimental laboratory of Technical University Berlin (TU Berlin), Germany. All subjects were recruited using ORSEE (Greiner, 2015) and the experiment was computerized using the software z-tree (Fischbacher, 2007). We ran a total of 32 sessions with 699 subjects overall. Each experiment lasted about 1.5h and subjects received a show up fee of 5 EUR. On average, subjects earned between 13 EUR and 18 EUR in total, depending on the treatment.

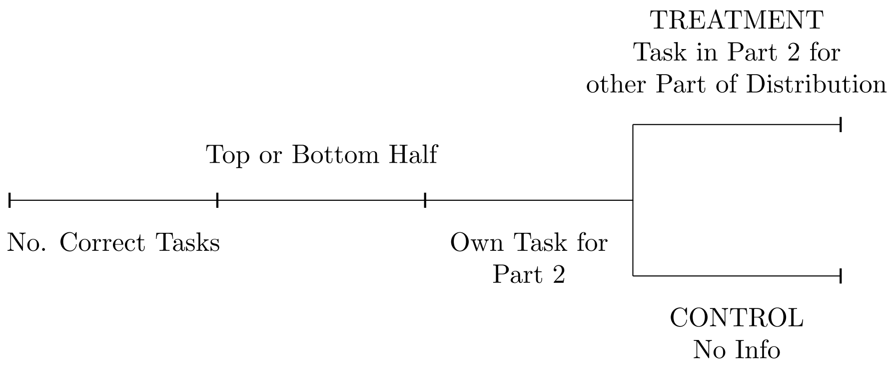
2.3.1 Experimental Procedure

Upon arrival at the laboratory, all participants sign a consent form (see Appendix 2.D) before entering the room where the experiment takes place. Just before entering the room, each subject draws his or her desk number and gets seated. Afterwards, written instructions for the experiment are handed out (see Appendix 2.D) and questions by the participants are answered. The experiment starts when there are no more questions. Following the experiment, subjects fill out a questionnaire and, afterwards, go to an adjacent room to receive their payment from an assistant.

All subjects complete two parts of a real effort task that take 30 minutes each. These two phases are separated by information the subjects receive (see Figure 2.1 for the general structure of the experiment). In this intermediate part, all subjects are told how many tasks they solved correctly, whether their performance is in the top or bottom half of their session's performance distribution and how part 2 of their real effort task would look like (see Figure 2.2). Crucially, participants that are subject to the treatment also were told how part 2 of the real effort task for the other half of the performance distribution

state that they felt better after donating.

Figure 2.2: Structure of the Information Section



would look like, whereas participants in the control group did not receive this information[8].

After the experiment concludes, subjects answer a questionnaire that consists of a computerized version of the German State-Trait Anger Expression Inventory-2 (STAXI-2)[9] (Rohrmann et al., 2013) as well as questions to assess subject characteristics.

During the whole experiment, participants are filmed by cameras that are positioned below their computer screen. They are informed of this already before signing up for the experiment, are reminded and sign a consent form before entering the lab. This procedure has been confirmed by the data protection officer of TU Berlin. The use of filming subjects during the experiment will be explained in the later subsection on the measurement of emotion.

2.3.2 The Task

The real effort task consists of typing strings that are shown on the subjects' computer screen[10]. Participants see their input in a textbox below the displayed string and can change their input until the moment when the ok-button is clicked and their string is submitted. In general, there are two different variants of the task: An easy version and a hard version[11].

In the easy version, all strings consist of 60 characters and have to be typed from the beginning of a string to its end. An example of such a string is given by

[8] All subjects saw the exact same number of screens but where participants in the treatment received information about the nature of other people's task, those in the control were asked to confirm that they are ready for part 2.

[9] We thank Hogrefe AG for the permission to use a computerized version of the STAXI-2.

[10] It was not possible to copy and paste the strings.

[11] Huck, Szech, and Wenner (2015) used the same task as our easy task in their experiment before.

Figure 2.3: Computer Screen for Hard Task

NXgCX7JHxYZj2cfBSd8JtkYp3LPcyDX8y8NNQhrzJfg22S2ACjC85EQ43B7L

The harder task is given by typing 120 character strings in reverse, i.e. from right to left[12]. An example of such a string is

Fm22cDQKgpgzv5Ez2SBSbAzuPcRbyDVkvqpJPjWbqHeCUFN2nu5D83RLSs
SH8hPMcbeGdyWbrqQ5E6a8xKcqtW6HtdAcFu9QEru7THV3umrg5S6QKrwmf9fY

All strings were shown in the same font size, centered on the screen and in one line (see Figure 2.3).

2.3.3 The Treatments

In total, we ran four different treatments. The general structure described in Figure 2.1 remains the same over all of those treatment variations and so does the main theme of the treatment: In part 2, the high performers are disadvantaged compared to the low performers but it is only the treated subjects that are made aware of this fact.

The baseline treatment, called "Start Easy", has all subjects starting out with the easy task. However, in part 2 of the real effort task, high types had to switch to the hard task. In the version called "Start Hard", all subjects begin with the hard task and only low types switch to the easy task in part 2. In both variants, the piece rate is held constant at 0.50 EUR for each correctly typed

[12]One subject used the strategy to type from left to right and use the keyboard to make the cursor jump left after each input. However, this did not seem to be a particular advantage.

string. In contrast, in the remaining two treatment variations, the difference between parts 1 and 2 is born out in the piece rate, while the task stays constant. In the variant “Start Easy Wage” all subjects start out with the easy task and a high piece rate of 0.50 EUR. In part 2, low types are again subject to the high piece rate and keep on working on the easy task while high types also solve the easy task but are paid a lower piece rate of 0.10 EUR[13]. Finally, “Start Hard Wage” has the hard task for all subjects in part 1 and 2 with a piece rate of 0.50 EUR for all subjects in part 1 and a switch to a higher piece rate of 3 EUR for low types in part 2[14]. All four variants of the experiment are summarized in Table 2.1.

In conducting different treatments that either vary the task or the piece rate, the experiment enables us to draw inference with regard to the question of whether individuals react differently to information about shocks to cost or revenue of effort for a comparison group.

Table 2.1: Variants of the Experiment

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Task Part 1	Easy	Hard	Easy	Hard
Change for	High Type	Low Type	High Type	Low Type
Change to	Hard Task	Easy Task	Low Wage	High Wage

2.3.4 Measuring Emotion

According to the definition in Section 2.2, an emotion consists of several components (and their synchronized changes) only one of those being facial expressions. However, the facial expression of emotions is a component of an emotion episode that is particularly suited to be studied in economic experiments. In contrast to other measures of emotion such as functional magnetic resonance imaging fMRI or facial electromyography (EMG), the facial expression can be videotaped and therefore be collected with a minimal interference of the experimenter with the participants. In addition, analyzing facial expressions has advantages over self-reports of emotion. Free form self-reports require that subjects find words suited to express their emotion in which lies the danger of heterogeneity in the ability to describe ones emotion verbally. In contrast, questionnaires designed to elicit

[13]The ratio of high and low piece rate corresponds to the ratio of average correct strings typed by high type participants in the easy and hard task.

[14]Again, the change in piece rate corresponds to the change in correctly typed strings between the easy and hard task.

emotions are often limited to the study of certain emotion (see e.g. the State-Trait Anger Expression Inventory Spielberger (1999)). Further, depending on the design of the experiment, self-reports can have the disadvantage that they are either answered at the end of the experiment at which time the emotional episode that has been triggered already ended or that the elicitation is conducted in timely proximity to the stimulus in which case the elicitation could interfere with the emotional episode itself.

In relying on video footage of facial expressions during the experiment, our experimental design permits us to directly measure the impact of information about a peer group's work environment on the expression of emotion. We analyze the video footage using the software Facereader Version 6. In addition, we employ the State-Trait Anger Expression Inventory 2 (STAXI-2) a questionnaire developed by psychologist Spielberger (1999) in the German adaptation by Rohrmann et al. (2013) at the end of the experiment to gain complementary information on subjects' dealing with emotion.

Facereader

Facereader is an automated facial coding (AFC) software that takes pictures and videos of people's faces as input and detects facial expressions. It does so in a three step procedure. First, a face is detected in the input material upon which, second, a 3D active appearance model (AAM) (see Cootes, Taylor, et al. (2004)) is constructed (Lewinski, den Uyl, & Butler, 2014). This AAM makes it possible to construct a model of the face even if the perspective is not fully frontal or lighting creates challenges through shadows on the face. Thirdly, a neural network that has been trained to detect emotion is employed to calculate probabilities and intensities of emotion (see Lewinski et al., 2014; Van Kuilenburg, Wiering, & Den Uyl, 2005). These emotion consist of Ekman (1984)'s six basic emotions, namely happy, sad, angry, surprised, scared, disgusted and neutral. In their study, Lewinski et al. (2014) show that Facereader[15] had an accuracy 88% in detecting target emotions from the Warsaw Set of Emotional Facial Expression Pictures (Olszanowski, Pochwatko, Kukliński, Ścibor-Rylski, & Ohme, 2008) and the Amsterdam Dynamic Facial Expression Set (Van Der Schalk, Hawk, Fischer, & Doosje, 2011) whereas humans achieved an accuracy of 85%. Notably, this high accuracy had been achieved on datasets that were not the one the software was trained on[16].

By attaching cameras to the subjects' computer screens, we were able to record participants' faces throughout the whole experiment. Using the software

[15] In the same version that was used in our experiment.

[16] Facereader was trained on the Karolinska Directed Emotional Faces (Lundqvist, Flykt, & Öhman, 1998)

mucap (Doyle & Schindler, 2015) we later on (offline) matched the z-tree stage of the experiment with the recorded video of these stages. For the videos' interpretation, we used Facereader's general model without calibration and analyzed all recorded material at every frame of the 24fps videos.

Although the software can deal with images that contain different perspectives and lighting situations[17] we took care to set up the laboratory so as to reduce heterogeneity in the video as far as possible. In doing so, chairs' backs were locked into an upright position and the height of the seat was set to the same level for all chairs. Computer screens were moved to the back of the desk and cameras were placed below them. The light settings of the cameras were adjusted, if necessary, to the time of the day. Similarly, shades were used to create light as homogeneous as possible at the desks close to the laboratory's windows.

In our analysis, we make use of the six basic emotions mentioned above, as well as a neutral state and measures of arousal and valence. Except for valence, all values for the emotions range between 0 and 1 with higher values indicating a more intensely expressed emotion. Further, different emotions can be present at the same time (all measure do not necessarily add up to one). The measure valence is constructed by the software as the difference between the strongest negative emotion and happy, the only positive emotion.

STAXI-2

The STAXI-2 is a questionnaire aimed at measuring different aspects of the experience, expression and control of anger. In its German adaptation, it consists of 51 items. In our study, we make use of the five major scales "State Anger", "Trait Anger", "Anger Expression-Out", "Anger Expression-In" and "Anger Control". State anger is a measure of the intensity of anger in a subject and its impulse to express anger[18]. Among the items for the state anger scale are the statements "Ich bin aufgebracht." (I am upset.) and "Ich könnte jemanden treten." (I could kick someone.) for which subjects had to chose between no agreement and high agreement on a 4-point scale. Further, trait anger measures the frequency with which anger is felt[19] and consists of items such as "Ich habe ein hitziges Temperament." (I am hot-tempered) or "Ich bin wütend, wenn ich etwas gut mache und schlecht beurteilt werde." (I am angry when I do a good job but am judged negatively). Anger expression-out is a measure for the

[17]This is, of course, only true to some extend. In particular, the interpretation of the facial model can change and cause different results depending on the perspective. A face is, e.g., interpreted as showing more anger when the camera is located in a higher position. It therefore matters for the results whether the camera is positioned on top or below the computer screen.

[18]The measure state anger takes values between 15 and 60.

[19]The measure trait anger takes values between 10 and 40.

frequency with which anger is expressed verbally or physically, whereas anger expression-in measures the frequency with which anger is felt but not expressed. These two scales consist of items such as “Ich verliere die Beherrschung.” (I lose control.) and “Ich fresse die Dinge in mich hinein.” (I bottle up feelings.)[20]. Lastly, anger control measure the frequency with which anger is controlled and is based on statements such as “Ich bemühe mich, meine Wut zu lindern.” (I try to ease my anger.)[21].

Although the disadvantages of eliciting emotion through self-reports at the end of the experiment have been discussed above, the STAXI-2 questionnaire can still provide useful information. In particular, as only one of the measures is concerned with the emotional state at the time. All other measures that will be included in the analysis are concerned with with the question of how the subjects typically deal with anger.

2.4 Results

2.4.1 Descriptive Statistics

In the following, descriptive results for the real effort tasks as well as for the different measures of emotion will be presented.

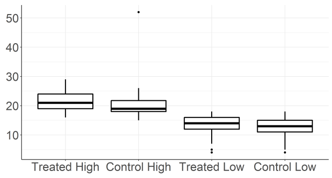
Start Easy

The average number of correctly typed strings in part 1 of the experiment, featuring the easy task, was 17. While those subjects classified as high types on average produced about 21 correct strings, those classified as low types typed an average of 13 strings correctly[22]. Comparing the productivity of all subjects in the treatment sessions with those in control sessions, no statistically significant difference can be found. However, the median number of correctly typed strings by treated high types exceed that of high types participants in the control by 2.

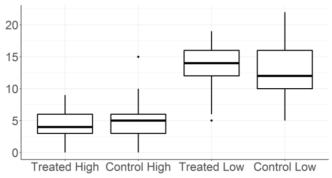
In part 2, as is expected from the harder task, the number of correctly typed strings of high types is, on average, lower than that of the low type subjects, who still were working on the easy task (see Panel (b) of Figure 2.4). The average number of correctly typed strings for all low types is about 14 and 5 for the high types. No significant differences can be found when comparing the number of correctly typed strings between treated and untreated subjects within the groups of high and low types. The median number of correctly typed strings is

[20]Both anger expression scales range between 8 and 32 in values.
[21]Anger control takes values between 10 and 40.
[22]The difference is significant on the 1% level in a Wilcoxon rank sum test.

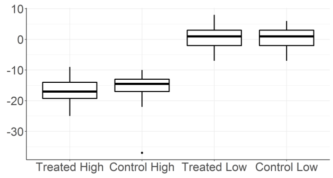
Figure 2.4: Boxplots of Correctly Typed Strings (Start Easy)



(a) Correct Strings (Part 1)



(b) Correct Strings (Part 2)



(c) Difference of Correctly Typed Strings

lower by 1 for the high types and larger by 2 for the low types in the treatment sessions as compared to the corresponding subjects in the control sessions.

As a consequence, the median productivity change is the same for low types in control and treatment sessions (median productivity increased by 1). However, at the median productivity for high types in treatment sessions dropped by 17 whereas it dropped by 14.5 for high types in the control sessions (see Panel (c) of Figure 2.4). The productivity change differs statistically significant with p-value 0.02 in a two-sided Wilcoxon rank sum test.

These results suggest that there is a negative treatment effect for high type subjects in terms of productivity but no treatment effect for low types.

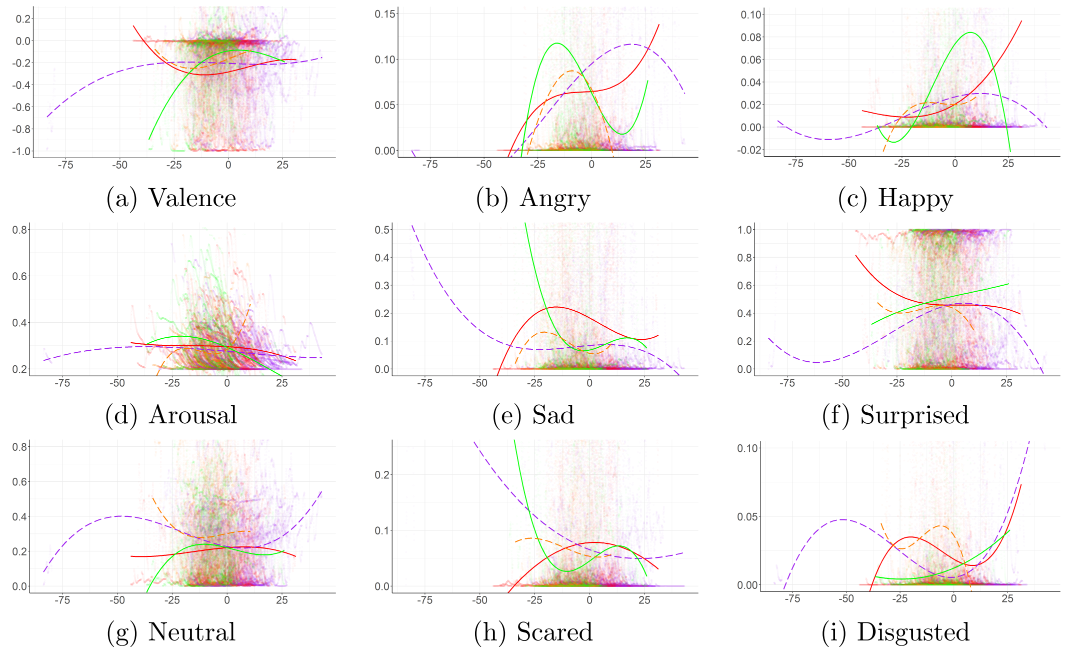
To describe the emotions participants went through during the experiment, we focus on two moments in time for the Facereader data and complement these with data from the STAXI-2 questionnaire which was answered at the end of the experiment. The baseline is given by the emotions shown when subjects face the screen where they are informed on how they will continue to work in part 2 of the real effort task ("Info Own") (see Figure 2.2 for the structure of the information section of the experiment). Until that point, high types in the treatment and high types in the control are in the exact same situation and the same is true for low types. These emotions are then compared to those shown while subjects face the next screen ("Info Others"). Crucially, on that screen, subjects in the treatment receive information on how the other part of the performance distribution will continue to work while participants in the control do not receive this information.

The emotions recorded by Facereader are plotted in Figure 2.5. Each vertical axis represents the intensity of each emotion and the horizontal axis represents time, with positive values indicating the time spent looking on the "Info

Others" screen and negative values for the time during "Info Own" screen[23]. Each (opaque) dot represents one observation and is assigned to one of the four groups: Treated High Type (red), Treated Low Type (Purple), Control High Type (Green) and Control Low Type (Orange). Added to the plots are fitted polynomials of degree 3.

[23] As subjects themselves chose when to click the ok button and leave a screen, the range of time values spent in each stage can differ between the groups.

Figure 2.5: Emotions During "Info Own" and "Info Others" (Start Easy)



(a) Valence (b) Angry (c) Happy

(d) Arousal (e) Sad (f) Surprised

(g) Neutral (h) Scared (i) Disgusted

Notes. Negative values on horizontal axis correspond to time during "Info Own" screen whereas positive values correspond to time during "Info Others" screen. Vertical axis captures intensity of Emotion. Each (opaque) circle is one observation. Lines are fitted polynomials of dregree 3. Solid Red : Treated Top, Dashed Purple: Treated Low, Solid Green: Control Top, Dashed Yellow: Control Low; N=95301

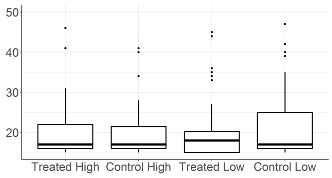
Panel (a) of Figure 2.5 shows valence, a measure that is constructed as the difference between the strongest negative emotion and happy (the only positive emotion) at every point in time. Comparing high type participants in treatment and control it can be seen that participants in the treatment show significantly lover values of valence (1% level, Wilcoxon rank sum test), both during the "Info Own" screen and the "Info Others" screen and measured as mean and median of the respective group. This can be interpreted as treated high types displaying a more negative mood as compared to their counterpart in the control. From one screen to the next, valence increases for both groups but less strongly for treated high types. For the low types, those in the control start out at a significantly lower level of valence than low type subjects in the treatment (1% level, Wilcoxon rank sum test) but this relation reversed for the "Info Others" screen (1% level, Wilcoxon rank sum test), as the participants from the treatment showed lover values of valence while it increased for subjects in the control. Again, this is born out in mean as well as median levels for valence. Therefore, the mood of participants takes a negative course when receiving information about a comparison group irrespective of whether this information reveals an advantage or a disadvantage.

One potential reaction high type participants in the treatment could show as a response to the information that they are disadvantaged compare to the low types is anger. As the fitted lines in panel (b) of Figure 2.5 suggests, high types in treatment start out at lower levels of anger but then exceed the anger levels or their control peers when receiving information of their disadvantagedness (1%level, Wilcoxon rank sum test). This pattern is also supported by mean and median anger levels for the two groups. In addition, also the anger levels of low type subjects in the treatment increase more strongly than those in the control group. However, their measured anger remains below that of low types in the control.

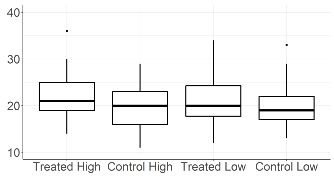
Perhaps surprisingly, median happiness increased for all groups except for treated low types. Nevertheless, treated high types show lower levels of happy than untreated high types during both screens (1%, Wilcoxon rank sum test for both comparisons). Treated low types' median happiness in "Info Own" is above median happiness of control low types (1% level, Wilcoxon rank sum test) but significantly lower than happy of untreated low types during "Info Others" (1% level, Wilcoxon rank sum test).

To complement the data received from participants' facial expressions, they filled out the State-Trait Anger Expression Inventory2 (Rohrmann et al., 2013) after the experiment ended. Figure 2.6 shows boxplots of the measures derived from the questionnaire. The results show that for high as well as low types there is no difference between those in treatment and control with regard to

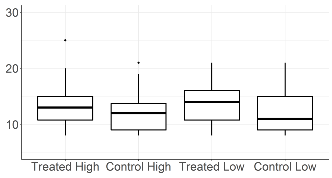
Figure 2.6: STAXI-2 Measures (Start Easy)



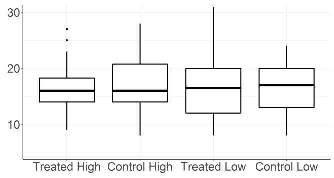
(a) State Anger



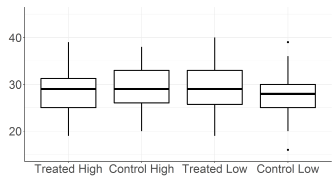
(b) Trait Anger



(c) Anger Expression (Out)



(d) Anger Expression (In)



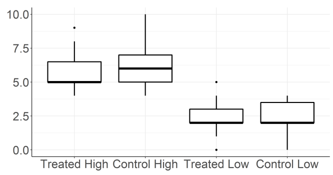
(e) Anger Control

the anger felt while completing the questionnaire (see Panel (a) of Figure 2.6). This is despite the fact that both high and low types in the treatment exhibit a greater tendency to express anger than subjects in their respective control group (see Panel (c))[24]. At the same time, treated low types report more anger control than untreated low types (significant at 10% level). This seemingly contradictory result can occur when subjects try to counter their expression of anger through anger control. In addition, treated high types exhibit a larger tendency to get angry than their peers in the control group, a difference that is significant on the 10% level.

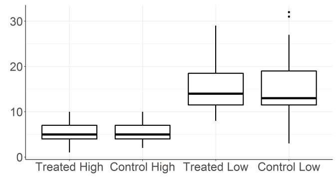
In summary, the descriptive statistics suggest that high types' reaction to the information of them being disadvantaged consists of a more negative mood in general and more intensely expressed anger as a direct response to the treatment. Also, high type subjects decreased their productivity as response to the treatment. On the other hand, low type subjects did not alter their productivity in response to their knowledge of being advantaged. This is the case although they as well show more negative emotion in response to the treatment as compared to the control group.

[24]For both high and low types the difference between treated and untreated subjects is significant on the 5% level in a Wilcoxon rank sum test.

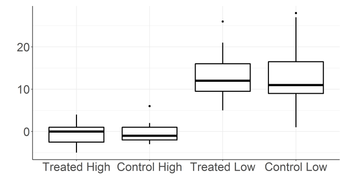
Figure 2.7: Correctly Typed Strings (Start Hard)



(a) Correct Strings (Part 1)



(b) Correct Strings (Part 2)



(c) Difference of Correctly Typed Strings

Start Hard

In contrast to the “Start Easy” variant of the experiment, in “Start Hard”, all subjects start out typing long strings backwards whereas only the low types switch to typing the shorter strings forward in the second part of the real effort task.

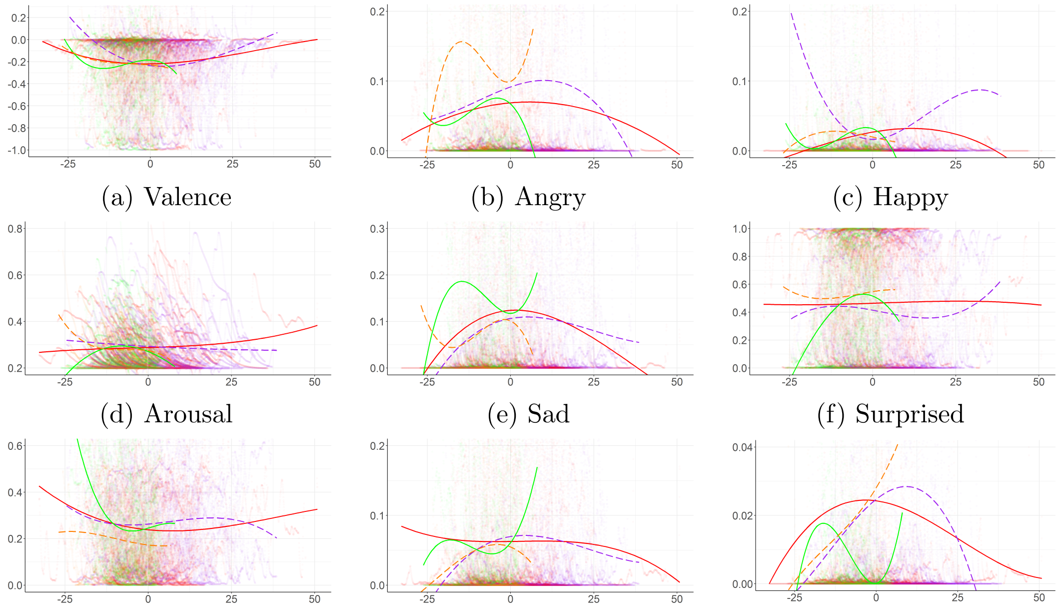
In part 1, treated high types were able to correctly type 5 strings at the median whereas high type individuals in the control do 6. During part 2, median production stayed the same for high types in the treatment while it dropped to the same number of 5 for the control. Comparing averages, both groups feature a similar drop in productivity given by 0.359 and 0.365 for treatment and control respectively. Low type subjects in treatment and control exhibit the same median and mean number of correct strings for part 1 of the task (2 and 2.462). After switching to the easier task in part 2, productivity increases to a median 14 correct strings for treated low types and 13 for low types in the control but this is no statistically significant difference. Therefore, it seems as if the treatment effect found in the “Start Easy” variant in the experiment did not survive the change in treatment.

Comparing subjects’ facial expressions during the “Info Own” and “Info Others” screens reveals that at first, median valence of treated high types is higher than that of high types in the control which is reversed during the “Info Others” screen, i.e. high type subjects’ mood is negatively affected by the treatment. During both screens, there is no statistically different valence between treated and untreated high types, though. For low types, valence is larger for treated than for untreated subjects during both screens and statistically significantly so (1% level in Wilcox rank sum test). However, valence decreases from one screen to the next and, in the median, does so more strongly for treated low types. Therefore, while the treatment effect concerning productivity did not carry over from “Start Easy” to “Start Hard”, the treatment still has a negative effect on the emotional measure valence for both low and high types.

As was the case in the “Start Easy” variant, the measure for angry is larger for treated high types than for untreated high types during both screens which is statistically significant on the 1% level (Wilcox rank sum test). In addition, the difference in angry between the two screens is larger for treated high types, i.e. compared to high types in the control, they get more angry during the “Info Others” screen. For the low types, the levels of angry are significantly lower for treated subjects than for the untreated during “Info Own” and “Info Others”. However, while there is no significant difference in angry for untreated between “Info Own” and “Info Others”, for the treated, angry is larger during “Info Others”.

Median happiness is lower for treated high types than for high types in the control (1% level, Wilcoxon rank sum test for both screens) and while it does increase in both groups, it does so less for the treated. On average, though, happiness of treated high types surpasses that of high types in the control during “Info Others” as can be seen in Panel (c) of Figure 2.8. For low types, treated subjects have higher levels of happy during both screens (significant at 1% level in Wilcoxon rank sum test) and while the level of happy decreases for subjects in the control, it stays constant for the treated subjects.

Figure 2.8: Emotions During "Info Own" and "Info Others" (Start Hard)



(a) Valence (b) Angry (c) Happy

(d) Arousal (e) Sad (f) Surprised

(g) Neutral (h) Scared (i) Disgusted

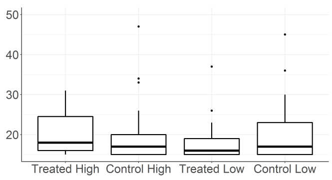
Notes. Negative values on horizontal axis correspond to time during "Info Own" screen whereas positive values correspond to time during "Info Others" screen. Vertical axis captures intensity of Emotion. Each (opaque) circle is one observation. Lines are fitted polynomials of dregree 3. Solid Red : Treated Top, Dashed Purple: Treated Low, Solid Green: Control Top, Dashed Yellow: Control Low; N=81053

In Figure 2.9, different measures of anger and attitudes towards ones anger are plotted based on subjects' responses to the STAXI-2 questionnaire. The current level of anger, state anger, was highest for treated high types with a median of 18 and mean of 22. At the same time, high types in the control exhibit median state anger of 17 and a mean of 19. There is a difference in this measure between the two groups that is statistically significant on the 10% level (Wilcoxon rank sum test). For low types, there is no statistically significant difference in state anger which amounts to a median of 16 for treated and 17 for untreated low types.

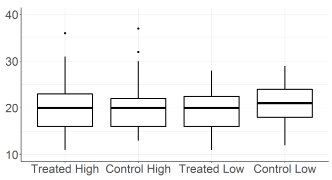
No statistically significant difference can be found with regard to trait anger which had median levels of 20 for all groups except untreated low types, which had a median trait anger of 21. Similarly, while there are small differences in median levels of anger expression and anger control between the groups, none of these is statistically significant.

Based on the above, subjects appear to react negatively to the treatment in terms of emotions expressed. However, in contrast to the "Start Easy" variant of the experiment, this reaction does not coincide with a change in productivity.

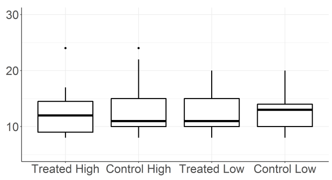
Figure 2.9: STAXI-2 Measures (Start Hard)



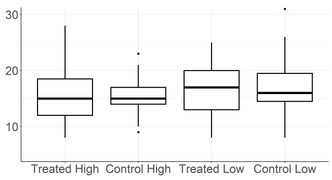
(a) State Anger



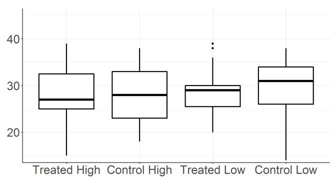
(b) Trait Anger



(c) Anger Expression (Out)

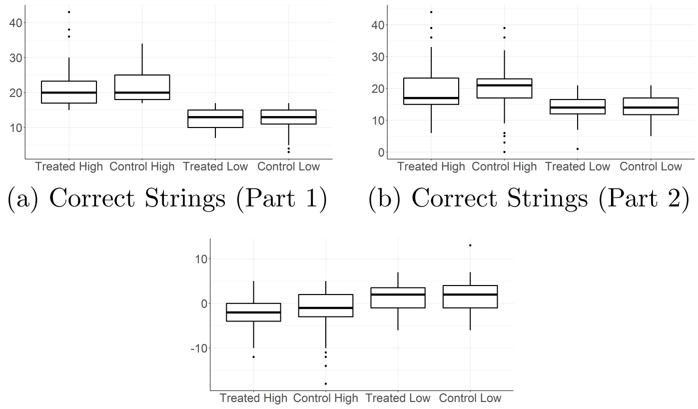


(d) Anger Expression (In)



(e) Anger Control

Figure 2.10: Correctly Typed Strings (Start Easy Wage)



(a) Correct Strings (Part 1) (b) Correct Strings (Part 2)

(c) Difference of Correctly Typed Strings

Start Easy Wage

Under the "Start Easy Wage" regime, all subjects in both parts of the real effort task type the short strings from beginning to end. However, while all subjects receive 0.50 EUR for each correct strings in part 1, in part 2 high types only receive 0.10 EUR while low types still earn 0.50 EUR for a correctly solved task.

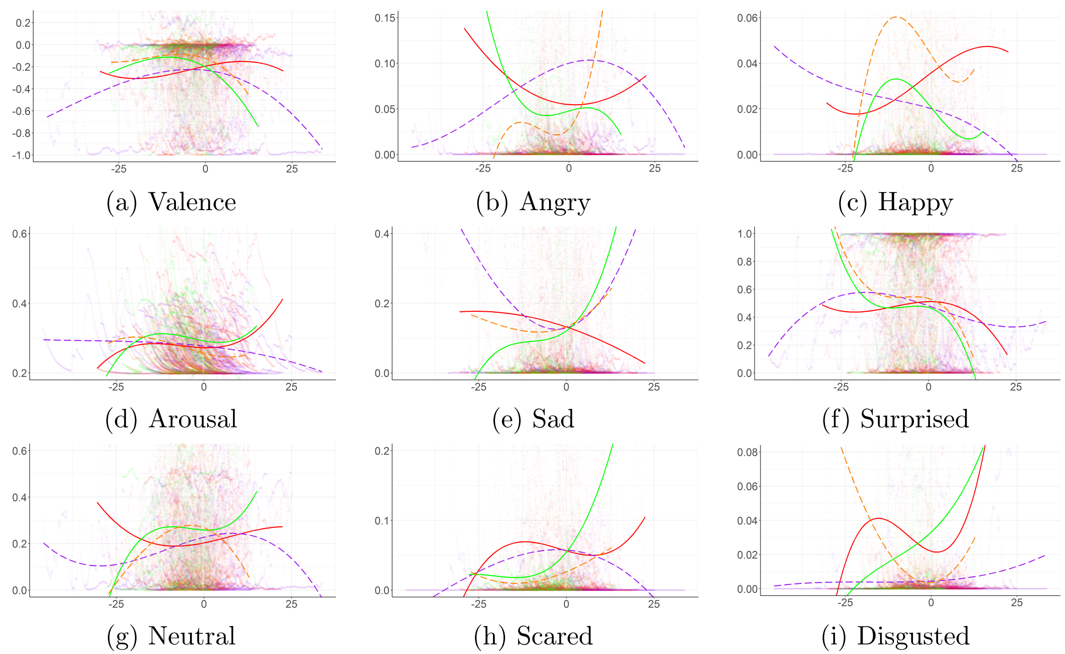
In part 1, high types produced a median 20 (mean 22) correct strings both in the treatment and the control. In part 2, treated high types correctly typed a median 17 strings correctly while high types participants in the control correctly produced a median 21 strings. However, due to some outliers the mean number of correct strings in part 2 is 20 for treatment as well as control. The differences in productivity in part 2 are not statistically significant in a Wilcox rank sum test. Treated as well as untreated low types increased their median number of correctly typed strings from 13 to 14. Based on these numbers, the negative treatment effect on high types receives weak support: While a negative effect is born out in the median number of correctly typed strings, there is no statistically significant difference in the productivity change between treated and untreated high types.

Turning to the facial expressions subjects exhibited during the "Info Own" and "Info Others" screen, it can be seen that treated high types had lower levels of valence during the "Info Own" screen and higher values of valence during the "Info Others" screen, both comparisons being statistically significant on the 1% level in a Wilcoxon rank sum test. The comparison of valence in treated and untreated low types is statistically significant at the 1% level (Wilcoxon rank sum test) as well with treated low types showing lower levels of valence during both information phases.

Concerning the measures of angry, untreated high types have higher levels of anger in “Info Own” than their treated comparison group, a difference that is statistically significant at the 1 % level (Wilcoxon rank sum test). During the “Info Others” screen, median levels of angry are again lower for treated high types, but comparing angry levels for treated and untreated high types in a Wilcoxon rank sum test gives a p-value of 0.1038. In addition, while the absolute decrease in median angry levels is larger for treated high types, their relative decrease in angry levels is smaller. In low types, treated subjects have higher levels of angry than their control peers which is statistically significant at the 1% level (Wilcoxon rank sum test) during both screens.

Both groups of high types show more happy in “Info Others” than in “Info Own” and statistically significantly so (1% level, Wilcoxon rank sum test) but treated high types are significantly more happy in “Info Own” but significantly less happy in “Info Others” than untreated high types (1% level, Wilcoxon rank sum test). With the low types, treated subjects exhibit lower levels of happy during both screens but while happy for untreated low types stays constant over the two screens, it is significantly lower for the treated high types during the second screen.

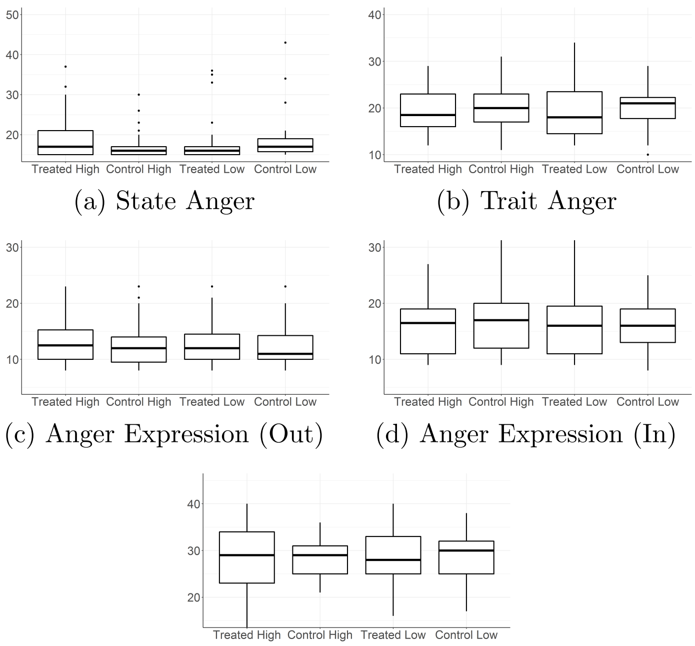
Figure 2.11: Emotions During “Info Own” and “Info Others” (Start Easy Wage)



(a) Valence (b) Angry (c) Happy
(d) Arousal (e) Sad (f) Surprised
(g) Neutral (h) Scared (i) Disgusted

Notes. Negative values on horizontal axis correspond to time during “Info Own” screen whereas positive values correspond to time during “Info Others” screen. Vertical axis captures intensity of Emotion. Each (opaque) circle is one observation. Lines are fitted polynomials of dregree 3. Solid Red : Treated Top, Dashed Purple: Treated Low, Solid Green: Control Top, Dashed Yellow: Control Low. N=65328

Figure 2.12: STAXI-2 Measures (Start Easy Wage)



(a) State Anger (b) Trait Anger

(c) Anger Expression (Out) (d) Anger Expression (In)

(e) Anger Control

Based on the questionnaire measure of anger and anger attitudes, it shows that treated high types are more angry at the end of the experiment than their untreated peers (p-value = 0.056, one-sided Wilcoxon rank sum test) and that the opposite it true for low types (p-value = 0.036, one-sided Wilcoxon rank sum test). This is despite the fact that there is no statistically significant difference in trait anger between the comparison groups. Similarly, there are statistically significant differences in the anger expression measures or anger control.

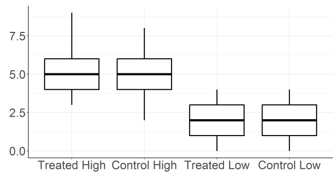
To sum up, based on the above descriptive statistics, there appears to be weak support for a negative treatment effect in terms of productivity in high type subjects. However, the different measures of emotion are somewhat inconclusive so far. While the Facereader data tends to suggest that that high types did not get more angry, their self-assessment at the end of the experiment tells a different story.

Start Hard Wage

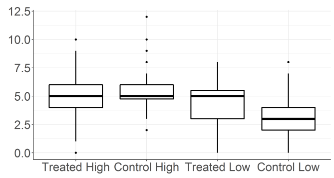
As in the "Start Easy Wage" variant, subjects in "Start Hard Wage" worked in the same type of task in both parts but this time it is the hard task. Also, low types' piece rate increased to 3 EUR while it stayed constant at 0.50 EUR for high types.

High types' median number of correct strings was 5 in the control as well as

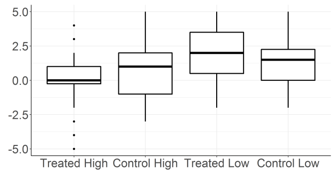
Figure 2.13: Correctly Typed Strings (Start Hard Wage)



(a) Correct Strings (Part 1)



(b) Correct Strings (Part 2)



(c) Difference of Correctly Typed Strings

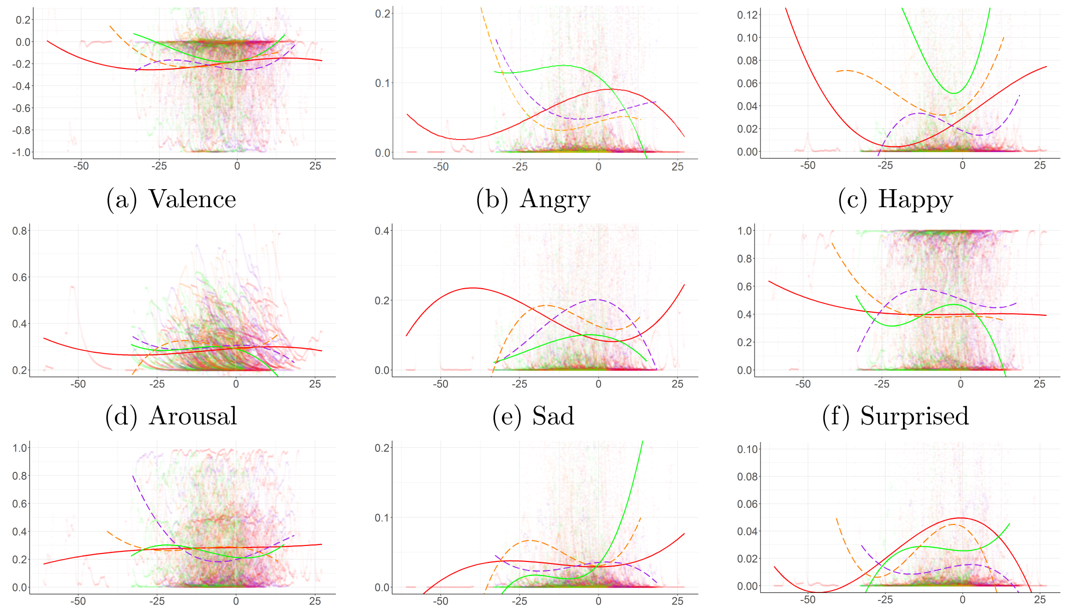
in the treatment in part 1 and part 2 of the real effort task. In the group of low types, both treated and untreated subjects started out with a median 2 correct strings in part 1. In part 2, treated low types increased that number to 5 while the median number of correctly typed strings for low types in the control was 3. This difference in correctly typed strings for low types in part 2 is statistically significant on the 5% level in a Wilcoxon rank sum test.

High types' valence is lower for treated than untreated subjects during "Info Own" (1% level, Wilcoxon rank sum test). While looking at the "Info Others" screen, however, valence increases for treated high types (1% level, Wilcoxon rank sum test) but does not do so for untreated high types. The two groups continue to differ in their valence (1% level, Wilcoxon rank sum test) with treated subjects having lower values of valence. Low types start out with levels of valence that do not differ statistically between treated and untreated subjects. Following the "Info Own" screen, treated low types exhibit lower levels of valence while valence for untreated low types increases (1%level, Wilcoxon rank sum test).

Angry was lower during "Info Others" than during "Info Own" for both treated and untreated high types. But it was larger for treated high types during both screens (1% level). In low type subjects, angry levels increased over time (1% level, Wilcoxon rank sum test). But while treated low types were more angry than untreated low types during "Info Own" (1% level, Wilcoxon rank sum test) the same comparison is statistically significant only on the 10% level (one-sided Wilcoxon rank sum test) during the "Info Others" screen.

Happiness levels of treated high types are below those of untreated high types during both screens (1% level, Wilcoxon rank sum test). However, while there is a strongly statistically significant increase in happy for treated high types (1% level, Wilcoxon rank sum test), the increase in untreated high types has a p-value of 0.03 in a one-sided Wilcoxon rank sum test. Treated low types get less happy from one screen to the next, whereas untreated low types get more happy (1% level, Wilcoxon rank sum test) and treated low types exhibit lower levels of happy during both screens (1% level, Wilcoxon rank sum test).

Figure 2.14: Emotions During "Info Own" and "Info Others" (Start Hard Wage)



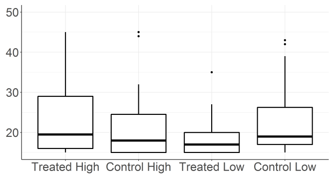
(a) Valence (b) Angry (c) Happy

(d) Arousal (e) Sad (f) Surprised

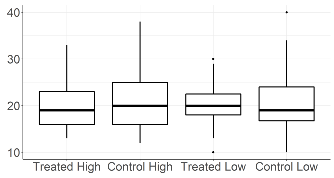
(g) Neutral (h) Scared (i) Disgusted

Notes. Negative values on horizontal axis correspond to time during "Info Own" screen whereas positive values correspond to time during "Info Others" screen. Vertical axis captures intensity of Emotion. Each (opaque) circle is one observation. Lines are fitted polynomials of degree 3. Solid Red : Treated Top, Dashed Purple: Treated Low, Solid Green: Control Top, Dashed Yellow: Control Low. N=91680

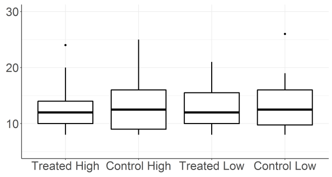
Figure 2.15: STAXI-2 Measures (Start Hard Wage)



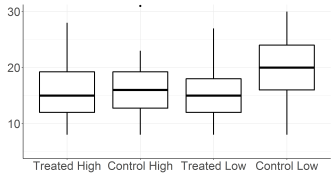
(a) State Anger



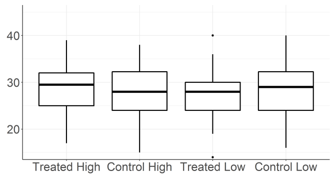
(b) Trait Anger



(c) Anger Expression (Out)



(d) Anger Expression (In)



(e) Anger Control

Based on the STAXI-2 measure of state anger, treated high types show larger anger levels than their untreated peers (p-value = 0.068, one-sided Wilcoxon rank sum test) with median levels of state anger of 19.5 for treated and 18 for untreated high types (mean: 25 vs 21). In addition, untreated low types have higher levels of state anger than treated low types (1%, one-sided Wilcoxon rank sum test) with median state anger of 19 for untreated low types compared 17 for treated low types (mean: 23 vs 18). Except for the measure anger expression in, there is no statistical difference between the comparison groups in trait anger, anger expression or anger control. In anger expression in, low types in the control exhibit significantly larger levels of anger expression in than treated low types (1% level, Wilcoxon rank sum test).

While a treatment effect with regard to the productivity of high types seems to be lacking, the descriptive statistics suggest there is a positive effect on low type individuals. At the same time, they appear to respond negatively to the treatment in terms of emotion although it should be noted that based on the STAXI-2 measure, they report less anger at the end of the experiment than untreated low types.

Comparison

Across treatments, the descriptive statistics show some support for a negative reaction in terms of productivity by high type subjects to the information that they are disadvantaged. This is based on the findings from the “Start Easy” and “Start Easy Wage” variants. For low type subjects, an increase in productivity due to the treatment has been found in the “Start Hard Wage” variant of the experiment.

In terms of emotion, a negative effect of the treatment on high types’ valence is found in the “Start Easy” and “Start Hard” variant. At the same time, a positive effect on anger is present. In contrast, a positive treatment effect for high types in terms of valence has been found in the “Start Easy Wage” variant. Low type subjects as well showed a decrease in valence due to the treatment in “Start Easy” and “Start Hard”. In addition, low type subjects exhibit a decrease in happy in the “Start Easy” and “Start Easy Wage” and “Start Hard Wage” variant. Besides, treated high types show higher levels in state anger than the comparison group in “Start Hard”, “Start Easy Wage” and “Start Hard Wage”. In contrast, treated low types show lower state anger than their comparison group in “Start Easy Wage” and “Start Hard Wage”.

2.4.2 Regressions

In this section, we extend the results presented in the previous section and analyzes the treatment effects in terms of productivity changes, emotional response to the treatment and the correlation of emotion and future performance.

Productivity Response to Treatment

The baseline model for estimating the difference-in-difference treatment effect is given by Equation 2.1 below. The number of correctly typed strings is regressed on a series of indicators that associate the observations with the four groups (Treated High Types, Control High Type, Treated Low Type, Control Low Type) and the two parts of the real effort task.

$$\begin{aligned} correct_{iP} &= \beta_0 + \beta_1 H + \beta_2 T + \beta_3 P \\ &\quad + \beta_4 H*T + \beta_5 H*P + \beta_6 T*P + \beta_7 H*T*P + \epsilon_{iP} \end{aligned} \tag{2.1}$$

with H, T, P being dummy variables. In particular, $H = 1$ if i is a high type subject, $T = 1$ if the subjects is part of the treatment and $P = 1$ if the observation comes from part 2 of the real effort task.

Based on the above, the estimator for the difference-in-difference results of low types is given by β_6 and by $\beta_6 + \beta_7$ for high types. To see this, note that the difference-in-difference estimator for low type subjects is constructed as

$$\begin{aligned} &E[correct_{iP}|H=0,T=1,P=1] - E[correct_{iP}|H=0,T=1,P=0] \\ &\quad - (E[correct_{iP}|H=0,T=0,P=1] - E[correct_{iP}|H=0,T=0,P=0]) \end{aligned}$$

and as such is given by

$$\beta_0 + \beta_2 + \beta_3 + \beta_6 - \beta_0 - \beta_2 - (\beta_0 + \beta_3 - \beta_0) = \beta_6$$

Similarly, for high type subjects, the difference-in-difference estimator is defined as

$$\begin{aligned} &E[correct_{iP}|H=1,T=1,P=1] - E[correct_{iP}|H=1,T=1,P=0] \\ &\quad - (E[correct_{iP}|H=1,T=0,P=1] - E[correct_{iP}|H=1,T=0,P=0]) \end{aligned}$$

which equals

$$\begin{aligned} &\beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6 + \beta_7 - \beta_0 - \beta_1 - \beta_2 - \beta_4 \\ &\qquad - (\beta_0 + \beta_1 + \beta_3 + \beta_5 - \beta_0 - \beta_1) = \beta_6 + \beta_7 \end{aligned}$$

Equation 2.1 will be estimated as a random effects model[25], i.e. we assume that the error term $\epsilon_{iP} = u_{iP} + c_i$ where u_{iP} is an idiosyncratic error term and c_i is an unobserved time-constant random variable with $E[\epsilon_{iP}|\mathbf{x_i}, c_i] = 0$ for both parts of the real effort task and $E[c_i|\mathbf{x_i}] = E[c_i]$ such that c_i is independent of regressors $\mathbf{x_i}$ in both parts of the experiment. Further remarks about the assumed error structure are in order. To illustrate these, Table 2.2 reports regression results based on Equation 2.1 with added controls. Column 1 presents standard errors based on the basic random effects assumption that idiosyncratic error terms u_{iP} have a constant and unconditional variance across time and that there is no correlation between u_i in part 1 and 2. Column 2 reports cluster robust standard errors with standard errors clustered on the individual level, whereas column 3 reports the results with robust standard errors clustered on the session level. While robust standard errors allow for heteroscedasticity in the error terms, clustering allows for correlation within the group of oberservations the cluster is defined on. While there might be reasons to believe that there is correlation within sessions, it poses the problem that there were only 8 sessions per variant of the experiment which is too few for a reasonable estimation of

[25] A Breusch-Pagan Lagrange Muliplier Test rejects the use of Pooled OLS.

the standard errors.

Table 2.2: Random Effects Panel Regression (Start Easy)

	#correct		
	No Cluster	Individual Cluster	Session Cluster
Treated	0.467	0.467	0.467
	(0.696)	(0.585)	(0.384)
High Type	6.927^{***}	6.927^{***}	6.927^{***}
	(0.724)	(0.855)	(0.562)
Part 2	0.622	0.622	0.622
	(0.554)	(0.522)	(0.511)
Treated*High Type	0.471	0.471	0.471
	(0.981)	(1.075)	(0.710)
Treated*Part 2	-0.081	-0.081	-0.081
	(0.771)	(0.706)	(0.668)
High Type*Part 2	-16.100^{***}	-16.100^{***}	-16.100^{***}
	(0.779)	(0.838)	(0.456)
Treated*High Type*Part 2	-1.295	-1.295	-1.295^{*}
	(1.088)	(1.090)	(0.688)
Time 1st correct	-0.009^{***}	-0.009^{***}	-0.009^{***}
	(0.002)	(0.002)	(0.002)
Female	0.369	0.369	0.369
	(0.452)	(0.409)	(0.501)
Semester	0.048	0.048	0.048
	(0.059)	(0.051)	(0.065)
No Math	-0.465	-0.465	-0.465
	(0.542)	(0.457)	(0.509)
(Intercept)	14.107^{***}	14.107^{***}	14.107^{***}
	(0.719)	(0.680)	(0.809)
# observations	374	374	374
# clusters	0	187	8
R^2	0.834	0.834	0.834

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, Random effects regression based on Equation 2.1. Robust standard errors in parentheses.

As shown above, the difference-in-difference estimate for low types is given

Table 2.3: Difference-in-Difference Productivity Effect (Start Easy)

	No Cluster	Individual Cluster	Session Cluster
Low Types	-0.081	-0.081	-0.081
	(0.771)	(0.706)	(0.668)
High Types	-1.376*	-1.376*	-1.376
	(0.767)	(0.830)	(0.921)

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Estimates from Table 2.2. Based on random effect regression. Robust standard errors in parentheses.

Table 2.4: Difference-in-Difference Productivity Effect

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Low Types	-0.081	0.068	-0.400	0.435
	(0.705)	(1.180)	(0.713)	(0.392)
High Types	-1.376*	0.066	0.116	-0.308
	(0.830)	(0.479)	(1.057)	(0.379)

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Estimates from Table 2.A.1 in Appendix 2.A. Based on random effect regression. Robust standard errors clustered on individual level in parentheses.

by the coefficient of the Treated*Part 2 interaction. Table 2.2 shows that irrespective of the modeling choice, the coefficient of Treated*Part 2 is not significantly different from 0, i.e. there is no treatment effect for low types with regard to productivity. For high type subjects, the difference-in-difference estimate is given by the sum of the Treated*Part 2 and Treated*High Type*Part 2 interactions. For clarity, both effects are reproduced in Table 2.3. The effect of knowing about being at a disadvantage is estimated as 1.376 fewer correct strings at an average 5 correctly typed strings in part 2. This estimate is significantly different from 0 on the 10% level for the specifications without robust standard errors and robust standard errors clustered on the individual level.

Table 2.4 reports the difference-in-difference estimates for all 4 variants of the experiment based on model 2.1 with added controls. The full regression table is given in Table 2.A.1 in Appendix 2.A. Based on the small number of sessions for each variant of the experiment the standard errors are robust and clustered on the individual level. It can be seen that in neither of the 4 variants, low type participants exhibit a treatment effect. What is more, it is indeed solely the treatment effect for high type subjects in the "Start Easy" variant of the experiment that shows a significant result.

Emotional Response to Treatment

Following the approach used for the descriptive statistics, inference will be based on the facial expressions recorded during the "Info Own" and "Info Others" screens. In particular, random effects models will be estimated where each of the six basic emotions as well as measures for valence, arousal and the neutral state are regressed on dummies for high type subjects (H) and being treated (T) as well as an indicator (S) for whether participants are looking at the "Info Own" or "Info Others" screen. In addition, interactions of all dummies H, T and S are added.

Similar to the previous section, the following model is estimated with robust standard errors clustered on the individual level

$$\begin{aligned} emotion_{it} = {} & \beta_0 + \beta_1 H + \beta_2 T + \beta_3 S \\ & + \beta_4 H * T + \beta_5 H * S + \beta_6 T * S + \beta_7 H * T * S + \epsilon_{it} \end{aligned} \tag{2.2}$$

Besides, controls are added to the regression model. These consist of subject characteristics such as gender, number of semesters at university, whether their studies included classes on mathematics and measures from the STAXI-2 questionnaire except for state anger and the mean value of the emotion in question during task 1, the time until the first correct string was typed and time itself.

Table 2.5 reports results for the "Start Easy" variant of the experiment. As in the previous section, difference-in-difference estimates of the treatment effects are given by the coefficients of the corresponding interactions. These are Treated*Info Others for low type subjects and the sum Treated*InfoOthers + Treated*Hightype*Info Others for high type subjects. For brevity, both group's treatment effects are reported in column 1 of Table 2.6.

For low type subjects, statistically significant treatment effects can be found for valence angry, the neutral state, and arousal whereas high type subjects exhibit a treatment effect with regard to the neutral state, surprised and arousal. Therefore, a change in facial expression can be found for both types of subjects with regard to the neutral state and arousal. However, while high type subjects get more neutral as well as aroused, the opposite is true for low type subjects.

What is more, the coefficient for Mean Emotion in Task 1 is positive for all measures of emotion and highly significant for 7 of the 9 measures which speaks for consistency in facial expression of subjects and their measurement by the Facereader software.

Table 2.5: Emotion Response (Start Easy)

	Valence	Angry	Neutral	Happy	Sad	Surprised	Scared	Disgusted	Arousal
Treated	0.049	-0.020	0.035	-0.003	-0.051	-0.027	0.028	-0.024*	0.003
	(0.050)	(0.026)	(0.032)	(0.015)	(0.038)	(0.064)	(0.028)	(0.013)	(0.017)
High Type	0.059	-0.008	-0.007	0.018	-0.018	0.023	0.007	-0.027*	0.039*
	(0.049)	(0.028)	(0.032)	(0.019)	(0.044)	(0.067)	(0.023)	(0.015)	(0.023)
Info Others	-0.041	-0.001	0.009	-0.014	0.029	-0.046	-0.002	-0.009	0.026*
	(0.037)	(0.025)	(0.019)	(0.012)	(0.025)	(0.036)	(0.011)	(0.015)	(0.014)
Treated*High Type	-0.212***	0.038	-0.112***	-0.029	0.165***	0.036	-0.023	0.040**	-0.024
	(0.069)	(0.038)	(0.043)	(0.021)	(0.058)	(0.083)	(0.038)	(0.018)	(0.026)
Treated*Info Others	-0.078*	0.062**	-0.063***	0.006	0.046	0.057	-0.006	0.009	-0.019
	(0.047)	(0.029)	(0.022)	(0.015)	(0.031)	(0.047)	(0.025)	(0.014)	(0.017)
High Type*Info Others	0.020	-0.005	-0.054*	0.008	-0.029	0.136**	0.022	-0.000	-0.066***
	(0.063)	(0.033)	(0.032)	(0.026)	(0.045)	(0.053)	(0.023)	(0.014)	(0.018)
Treated*High Type*Info Others	0.048	-0.047	0.122***	-0.000	-0.019	-0.215***	0.020	-0.023	0.071***
	(0.081)	(0.040)	(0.039)	(0.029)	(0.058)	(0.072)	(0.033)	(0.017)	(0.024)
Mean Emotion Task 1	0.390***	0.472***	0.486***	0.346	0.395***	0.474***	0.491***	0.291	0.395***
	(0.059)	(0.060)	(0.066)	(0.244)	(0.095)	(0.066)	(0.090)	(0.182)	(0.105)
Trait Anger	-0.002	-0.001	-0.000	0.000	-0.001	-0.002	0.005*	-0.002**	-0.000
	(0.004)	(0.002)	(0.003)	(0.001)	(0.003)	(0.005)	(0.003)	(0.001)	(0.001)
Anger Out	0.007	-0.000	-0.004	0.001	-0.004	0.012	-0.003	0.000	-0.001
	(0.006)	(0.003)	(0.004)	(0.001)	(0.005)	(0.008)	(0.003)	(0.002)	(0.002)
Anger In	-0.002	0.001	0.002	-0.002*	0.002	-0.005	-0.002	-0.000	-0.001
	(0.004)	(0.002)	(0.002)	(0.001)	(0.003)	(0.005)	(0.002)	(0.001)	(0.001)
Anger Control	0.004	-0.001	-0.003	0.003	-0.000	0.007	-0.001	-0.002	0.001
	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.005)	(0.001)	(0.001)	(0.002)
Time 1st correct	-0.000*	0.000	-0.000***	0.000	0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.016	-0.018	0.007	0.000	0.020	-0.028	0.030*	-0.009	0.010
	(0.038)	(0.022)	(0.026)	(0.011)	(0.036)	(0.050)	(0.017)	(0.009)	(0.016)
Age	0.006*	-0.004*	-0.002	0.001	0.001	0.006	-0.002	-0.001	0.000
	(0.004)	(0.002)	(0.003)	(0.001)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)
Semester	0.002	-0.000	0.006*	-0.001	-0.004	-0.005	0.001	-0.000	-0.000
	(0.004)	(0.002)	(0.003)	(0.001)	(0.004)	(0.006)	(0.002)	(0.001)	(0.002)
No Math	-0.111***	0.043	-0.017	-0.017*	0.022	-0.037	0.027	0.015	0.005
	(0.041)	(0.028)	(0.033)	(0.010)	(0.039)	(0.055)	(0.026)	(0.012)	(0.018)
Time	0.004***	-0.001	0.001	0.001*	-0.003***	0.001	-0.001*	0.001**	-0.001***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
(Intercept)	-0.213	0.111	0.305***	-0.021	0.043	-0.022	-0.040	0.149**	0.171***
	(0.173)	(0.094)	(0.106)	(0.067)	(0.113)	(0.215)	(0.088)	(0.069)	(0.063)
# observations	94,853	94,853	94,853	94,853	94,853	94,853	94,853	94,853	94,853
# clusters	173	173	173	173	173	173	173	173	173
R^2	0.129	0.267	0.267	0.030	0.133	0.205	0.223	0.049	0.104

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effects regression based on Equation 2.2. Robust standard errors clustered on individual level in parentheses.

To check in how far the treatment effect on emotions carry over to the other variants of the experiments, Table 2.6 compares the treatment effects for each emotion measure across the four different variants of the experiment. The full tables are reported in Tables 2.B.1 to 2.B.9.

Table 2.6: Difference-in-Difference Emotion Response

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
		Valence		
Low Types	-0.078*	0.073	-0.041	-0.066
	(0.047)	(0.062)	(0.041)	(0.056)
High Types	-0.030	-0.047	0.145**	0.046
	(0.069)	(0.054)	(0.058)	(0.057)
		Angry		
Low Types	0.062**	-0.003	0.021	0.030**
	(0.029)	(0.052)	(0.030)	(0.012)
High Types	0.014	0.001	0.040*	0.014
	(0.028)	(0.039)	(0.021)	(0.031)
		Neutral		
Low Types	-0.063***	0.013	0.056*	0.025
	(0.022)	(0.033)	(0.030)	(0.032)
High Types	0.058*	-0.035	0.009	0.043
	(0.033)	(0.038)	(0.032)	(0.040)
		Happy		
Low Types	0.006	0.020	0.002	-0.032
	(0.015)	(0.022)	(0.019)	(0.022)
High Types	0.006	0.012	0.031*	0.030
	(0.027)	(0.019)	(0.017)	(0.028)
		Sad		
Low Types	0.046	-0.032	0.049	0.002
	(0.031)	(0.033)	(0.033)	(0.039)
High Types	0.027	0.069*	-0.081*	-0.017
	(0.054)	(0.039)	(0.042)	(0.039)
		Surprised		
Low Types	0.057	0.026	-0.092*	-0.015
	(0.047)	(0.073)	(0.052)	(0.047)
High Types	-0.158***	-0.009	0.026	-0.010
	(0.053)	(0.069)	(0.053)	(0.048)
		Scared		
Low Types	-0.006	-0.021	-0.032*	0.008
	(0.025)	(0.021)	(0.018)	(0.018)
High Types	0.014	-0.006	-0.037	-0.007
	(0.022)	(0.024)	(0.041)	(0.012)
		Disgusted		
Low Types	0.009	0.015	0.000	-0.008
	(0.014)	(0.016)	(0.004)	(0.009)

High Types	-0.014	0.014***	-0.032	-0.014
	(0.009)	(0.005)	(0.024)	(0.014)
			Arousal	
Low Types	-0.019	-0.016	0.005	0.018
	(0.017)	(0.019)	(0.017)	(0.019)
High Types	0.052***	0.064***	0.011	0.041***
	(0.017)	(0.023)	(0.014)	(0.015)

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Difference-in-difference estimates of emotion change from "Info Own" to "Info Others". All estimates are based on random effect regression of Equation 2.2. Robust standard errors clustered on individual level in parentheses. Full regression tables are presented in Tables 2.B.1 to 2.B.9 in Appendix 2.B.

For Valence, the top panel of Table 2.6 shows that low type subjects show a negative effect on valence in the "Start Easy" variant that is marginally significant. In addition, there is a positive effect of ones awareness of being disadvantaged in the "Start Easy Wage" variant that is significant on the 5% level.

While the measure for valence is an aggregate and therefore might lack treatment effects, angry is measured directly by Facereader. What is more, getting angry seems to be a plausible reaction for high type subjects in response to the information defining the treatment. In addition, by including measures from the STAXI-2 questionnaire, they not only serve the purpose of controlling for subject characteristics, but could show in how far measure like anger control are correlated with the expression of anger in the experiment[26]. High type subjects in the variant "Start Easy Wage" reacted with more expressed anger to the treatment. However, the other three variants of the experiment fail to show a similar positive and significant effect for high type subjects. Perhaps surprisingly, in two of the four variants, low type subjects' reactions showed more anger in response to the treatment. They expressed anger as response to the information that high type subjects will receive a harder task in part 2 as well as to the information that they themselves receive 6 times the piece rate that high type participants receive in part 2.

For the neutral state, the variant "Start Easy" of the experiment shows a different reaction from high and low type subjects. While low type subjects' response to the treatment is given by the expression of less neutral state, high type subjects' facial expression show more neutral in response to the treatment.

Intuitively, happy could be the mirror image of angry in so far as low type subjects could be assumed to express happiness as response to knowing that they are advantaged compared to high type subjects. This is not born out in

[26]The various measures of attitudes towards anger from the STAXI-2 questionnaire do not show a clear correlation with the expression of anger during the two tested screens of the experiment.

the data, though. Rather, in one variant, it is high type subjects who react positively to the treatment. In addition, high type participants also expressed less sadness in the "Start Easy Wage" variant.

Although the treatment might have had the potential to surprise subjects, it did not seem to do so. In contrast, in two variants of the experiments, it was actually subjects from the control group that increased their surprise more than the corresponding treatment group among high and low types. This is even though their screen just said "Please confirm that you are ready for part 2 of the experiment".

Based on the treatment, neither low nor high type subjects got scared. But in the "Start Hard" variant, high type subjects got disgusted as they were informed that low types were able to switch to the easier task.

The most consistent (across variants of the experiment) emotional reaction to the treatment can be found in arousal. For high type subjects, the information on how low type subjects work in part 2 increased arousal in 3 of the four variants on a 1% level of statistical significance. For low type subjects, though, arousal did not change at a statistically significant level.

Emotion and Productivity

Last but not least, we will explore the question of whether there is a correlation between facial expressions during the information screens and productivity in part 2. To this end, we estimate the following model

$$correct_{iP} = \mathbf{Treated} * \mathbf{Hightype} * \mathbf{Part2} * \mathbf{DiffMeanEmo}_{iP}\beta + \epsilon_{iP} \quad (2.3)$$

where $\mathbf{Treated} * \mathbf{Hightype} * \mathbf{Part2} * \mathbf{DiffMeanEmo}$ is a vector containing variables for the main effects and all interactions of the three dummy variables Treated, High Type and Part 2 as well as DiffMeanEmo, which is continuous. In particular, Emo refers to each one of the nine measures of emotion that Facereader returns, i.e. valence, angry, neutral, happy, sad, surprised, scared, disgusted and arousal. Further, the Diff Mean refers to the mean of each emotion during the "Info Others" and "Info Own" screen and the difference between the two. In addition, controls are added which include the mean of the emotion in question during task 1 of the experiment, the duration until the first task was solved correctly, a dummy for gender, whether the subject's curriculum includes classes involving math, their semester and the STAXI-2 measures trait anger, anger control, anger expression in, anger expression out.

In an additional specification, the model to be estimated is given by

$$correct_{iP} = \textbf{Treated} * \textbf{Hightype} * \textbf{Part2} \\ + \textbf{Part2} * \textbf{DiffMeanEmo}_{iP}\beta + \epsilon_{iP} \quad (2.4)$$

such that DiffMeanEmo is only interacted with Part 2 and not with the dummies for Treated and Hightype. The effect of DiffMeanEmo on the number of correct strings in part 2 that comes from this specification is referred to as ALL in the regression tables in contrast to the estimates for the four sub groups participants.

As before, all regression results reported are random effects regressions with robust standard errors clustered on the individual level.

For the "Start Easy" variant, Table 2.8 shows the estimate of each emotion's impact on part 2 productivity for the four subject groups and the ALL specification. This shorter table is derived from Table 2.7 below. According to Table 2.8, the effect of emotion on productivity is not strongly robust across the four groups of subjects. Nevertheless, all estimates for the effect of angry on part 2 productivity are positive but only in case of Treated Low Types it is statistically significant as well. The effect of an increase in angry for all subjects is estimated to be positive as well, with a p-value of 0.0504. Therefore, it seems that the expression of anger and possibly the feeling of anger seem to be associated with increased productivity. Interestingly, treated low type subjects not only exhibit a positive association between anger and productivity but also between happy and productivity which might suggest that people can be motivated in different ways. In turn, subjects who are not moved emotionally might not care about the experiment and its design features and therefore show lower productivity. This is backed by a statistically significant negative effect of the intensity of the neutral state on productivity that was found for low type subjects.

Table 2.7: Effect of Emotion Response to Treatment on Productivity (Start Easy), Full Table

	Valence	Angry	Neutral	Happy	Sad	Surprised	Scared	Disgusted	Arousal
Treated	0.711	0.464	0.737	0.857	0.598	0.690	0.784	0.768	0.921
	(0.680)	(0.726)	(0.662)	(0.662)	(0.701)	(0.677)	(0.710)	(0.701)	(0.681)
High Type	7.142***	7.179***	7.141***	7.128***	6.996***	7.336***	7.014***	7.081***	7.024***
	(1.009)	(1.070)	(1.027)	(1.076)	(0.928)	(1.155)	(1.050)	(1.040)	(0.887)
Part 2	0.708	0.754	0.723	0.714	0.685	0.703	0.675	0.732	0.674
	(0.572)	(0.585)	(0.568)	(0.574)	(0.583)	(0.579)	(0.585)	(0.573)	(0.566)
Treated*High Type	0.594	0.786	0.611	0.484	0.819	0.193	0.667	0.664	0.504
	(1.175)	(1.307)	(1.253)	(1.290)	(1.085)	(1.399)	(1.293)	(1.287)	(1.119)
Treated*Part 2	0.277	0.110	-0.068	0.275	0.283	0.125	0.258	0.439	0.086
	(0.757)	(0.812)	(0.792)	(0.754)	(0.773)	(0.765)	(0.795)	(0.766)	(0.766)
High Type*Part 2	-16.176***	-16.207***	-16.068***	-16.176***	-16.128***	-16.214***	-16.091***	-16.148***	-16.056***
	(0.943)	(0.936)	(0.924)	(0.952)	(0.935)	(1.035)	(0.926)	(0.913)	(0.885)
Treated*High Type*Part 2	-1.657	-1.525	-1.425	-1.596	-1.674	-1.463	-1.687	-1.870	-1.555
	(1.195)	(1.225)	(1.207)	(1.207)	(1.200)	(1.271)	(1.202)	(1.180)	(1.163)
Difference Mean Emotion	0.783	1.390	-9.210**	5.692	-0.605	4.591	0.995	-1.512	-1.350
	(1.293)	(3.512)	(4.661)	(4.109)	(1.385)	(3.119)	(6.727)	(5.557)	(5.507)
Treated*Diff. Mean Emotion	-0.844	4.456	6.943	7.554	-0.057	-5.888*	0.029	-0.665	14.736
	(2.199)	(4.355)	(5.777)	(7.699)	(3.924)	(3.519)	(6.897)	(17.510)	(10.400)
High Type*Diff. Mean Emotion	-5.162	2.494	9.310	-11.211	9.309	-10.760**	2.102	-6.035	1.012
	(4.071)	(4.238)	(5.790)	(10.512)	(9.572)	(5.377)	(7.595)	(8.522)	(9.597)
Part 2*Diff. Mean Emotion	-0.816	2.474	-3.230	-0.045	1.069	-0.843	-1.570	1.929	7.319
	(2.128)	(4.838)	(4.528)	(4.839)	(3.152)	(2.948)	(4.112)	(3.887)	(6.800)
Treated*High Type*Diff. Mean Emotion	6.086	-4.760	-5.305	5.281	-8.004	11.919**	-7.306	5.239	-10.675
	(4.761)	(6.031)	(7.508)	(13.636)	(10.891)	(5.797)	(8.692)	(18.786)	(13.435)
Treated*Part 2*Diff. Mean Emotion	0.248	0.508	-5.741	-2.275	0.495	4.005	0.185	-18.916*	-24.865**
	(2.645)	(5.802)	(6.274)	(10.201)	(4.581)	(3.246)	(4.401)	(10.386)	(11.562)
High Type*Part 2*Diff. Mean Emotion	3.820	-5.345	4.861	5.720	-7.744	2.445	6.030	10.662	-6.831
	(3.671)	(5.571)	(4.999)	(8.292)	(8.387)	(4.242)	(6.185)	(7.223)	(9.512)
Treated*High Type*Part 2*Diff. Mean Emotion	-4.712	-0.230	3.295	-11.067	7.093	-5.794	-4.559	7.406	23.312
	(4.539)	(8.163)	(7.969)	(13.728)	(9.257)	(5.167)	(8.308)	(12.197)	(14.586)

Mean Emotion Task 1	-0.243	-0.992	0.167	13.776	2.551	-0.054	-1.366	-5.437*	1.015
	(1.624)	(1.026)	(1.066)	(8.574)	(4.268)	(0.658)	(1.960)	(2.810)	(3.294)
Trait Anger	-0.056	-0.061	-0.065	-0.082*	-0.059	-0.073*	-0.071	-0.073	-0.060
	(0.049)	(0.047)	(0.043)	(0.042)	(0.047)	(0.044)	(0.047)	(0.045)	(0.046)
Anger In	-0.027	-0.038	-0.041	-0.028	-0.021	-0.077	-0.028	-0.038	-0.031
	(0.055)	(0.062)	(0.061)	(0.055)	(0.056)	(0.068)	(0.062)	(0.062)	(0.058)
Anger Out	-0.096	-0.074	-0.088	-0.080	-0.088	-0.046	-0.079	-0.069	-0.086
	(0.101)	(0.082)	(0.079)	(0.083)	(0.083)	(0.069)	(0.085)	(0.085)	(0.089)
Anger Control	-0.022	-0.016	-0.040	-0.020	-0.030	-0.002	-0.028	-0.020	-0.020
	(0.052)	(0.046)	(0.047)	(0.044)	(0.048)	(0.046)	(0.047)	(0.047)	(0.049)
Time 1st correct	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.009***	-0.008***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female	0.454	0.396	0.419	0.259	0.555	0.666*	0.374	0.342	0.357
	(0.427)	(0.458)	(0.431)	(0.464)	(0.421)	(0.401)	(0.434)	(0.441)	(0.474)
Semester	0.046	0.059	0.024	0.028	0.032	0.043	0.039	0.048	0.047
	(0.057)	(0.058)	(0.056)	(0.054)	(0.062)	(0.056)	(0.057)	(0.054)	(0.057)
No Math	-0.483	-0.450	-0.594	-0.356	-0.477	-0.622	-0.517	-0.320	-0.467
	(0.550)	(0.500)	(0.462)	(0.488)	(0.530)	(0.510)	(0.539)	(0.557)	(0.505)
(Intercept)	17.122***	17.127***	17.987***	17.484***	17.175***	17.364***	17.572***	17.302***	16.908***
	(2.336)	(2.219)	(2.376)	(2.215)	(2.122)	(2.240)	(2.328)	(2.319)	(2.320)
# observations	324	324	324	324	324	324	324	324	324
# clusters	162	162	162	162	162	162	162	162	162
R^2	0.846	0.845	0.846	0.845	0.846	0.846	0.843	0.845	0.845

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.3 with robust standard errors clustered on individual level in parentheses.

Table 2.8: Effect of Emotion Response to Treatment on Productivity (Start Easy)

	Valence	Angry	Neutral	Happy	Sad	Surprised	Scared	Disgusted	Arousal
Treated High Type	-0.596	0.987	0.924	-0.352	1.554	-0.325	-4.095	-1.893	2.658
	(1.543)	(3.151)	(2.204)	(3.515)	(1.525)	(1.147)	(3.62)	(1.616)	(3.539)
Control High Type	-1.374	1.013	1.732	0.155	2.028	-4.568***	7.556**	5.044	0.15
	(1.314)	(1.763)	(3.033)	(2.876)	(2.551)	(1.387)	(3.732)	(3.551)	(4.33)
Treated Low Type	-0.629	8.828***	-11.237**	10.925**	0.901	1.865	-0.361	-19.164*	-4.16
	(1.593)	(3.016)	(4.482)	(4.616)	(2.628)	(1.673)	(1.698)	(10.98)	(9.832)
Control Low Type	-0.033	3.864	-12.44**	5.646	0.463	3.747	-0.575	0.417	5.969
	(2.127)	(2.806)	(6.008)	(3.719)	(3.29)	(4.278)	(5.308)	(6.048)	(7.619)
ALL	-0.711	2.94*	-2.666	3.473	1.256	-0.728	0.14	-1.319	1.975
	(0.812)	(1.503)	(1.664)	(2.243)	(1.174)	(0.905)	(1.508)	(2.434)	(2.694)

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Estimates in first 4 rows based on random effect regressions in Table 2.7. Estimates in last row based on random effects regressions reported in column 1 of Tables 2.C.10 to 2.C.18 in Appendix 2.C. Robust standard errors clustered on individual level in parentheses.

In a next step, we will compare in how far the results from the "Start Easy" variant are robust with regard to our variations of the experiment. To do so, Table 2.9 presents the estimates for the association of a change in emotion between the "Info Own" and "Info Others" screen with part 2 productivity.

As can be seen in Table 2.9 high type participants in the treatment show a positive association between valence and productivity in the "Start Hard" and "Start Easy Wage" variant of the treatment. The same is true for low type subjects in the treatment but for them, the coefficients are not significantly different from zero.

Panel 2 of Table 2.9 reports results on the effect of getting more angry from the "Info Own" screen to the "Info Others" screen on part 2 productivity. As reported above, in the "Start Easy" variant of the experiment all groups show a positive effect of getting more angry on productivity. This positive effect is significant on the 1% level for treated low types and close to being significant on the 5% level for all subjects. However, in all other variants of the experiment, it seems as if the effect of increased anger on productivity is rather negative. Therefore, a general conclusion of the effect of anger on productivity is hard to come by.

The effect of retaining a neutral state seems to differ between high and low types, though few estimates are significantly different from zero. Still, for high type subjects the majority of estimates are positive, whereas the majority of estimates for low types is negative.

Based on the estimates in the panel on happy in Table 2.9, in most cases there might be a negative effect of becoming more happy on productivity. However, in those cases where the effect is significantly different from zero the effect is positive for treated subjects but negative for subjects from the control. This would be consistent with people in the control who dislike the experiment being happy that the experimenter does not ask them for more unpleasant things and afterwards enjoy the quite life and slack off during part 2. In contrast, those in the treatments that get more happy do so because of the information they receive, i.e. based on characteristics of the experiment, and might therefore be more prone to exert effort afterwards.

For both, sad and surprised, the estimates are positive and negative and mostly not significantly different from zero. Those that are significant are negative. One might therefore conclude that it is probably not the case that inducing sadness or surprise increases productivity.

Table 2.9: Effect of Emotion Response to Treatment on Productivity

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
		Valence		
Treated High Type	-0.596	3.276**	9.917**	0.443
	(1.543)	(1.483)	(3.852)	(1.559)
Control High Type	-1.374	-0.637	-1.122	-0.019
	(1.314)	(1.281)	(3.812)	(0.692)
Treated Low Type	-0.629	2.953	0.142	-0.315
	(1.593)	(3.313)	(3.069)	(1.219)
Control Low Type	-0.033	-0.405	-1.791	-2.179***
	(2.127)	(5.409)	(5.457)	(0.619)
ALL	-0.711	1.349	3.404	-0.64
	(0.812)	(1.801)	(2.36)	(0.616)
		Angry		
Treated High Type	0.987	-1.191	-6.82	-3.695
	(3.151)	(1.769)	(4.839)	(3.424)
Control High Type	1.013	-3.64**	5.962	-2.829*
	(1.763)	(1.53)	(11.974)	(1.515)
Treated Low Type	8.828***	-1.969	-19.627***	4.457
	(3.016)	(4.354)	(7.063)	(4.914)
Control Low Type	3.864	-5.757	-2.143	1.823
	(2.806)	(4.156)	(6.506)	(1.947)
ALL	2.94*	-3.236*	-7.542*	-1.824
	(1.503)	(1.928)	(3.882)	(1.819)
		Neutral		
Treated High Type	0.924	1.556	14.38*	-1.37
	(2.204)	(3.236)	(7.536)	(2.095)
Control High Type	1.732	1.758	-12.257	2.808
	(3.033)	(2.453)	(8.059)	(1.886)
Treated Low Type	-11.237**	4.086	-6.28	-0.19
	(4.482)	(3.45)	(4.39)	(2.313)
Control Low Type	-12.44**	-13.402	-1.948	-1.951
	(6.008)	(9.132)	(6.242)	(2.437)
ALL	-2.666	0.545	-1.321	-0.313
	(1.664)	(2.215)	(3.569)	(1.13)
		Happy		
Treated High Type	-0.352	7.072***	-1.092	-2.714
	(3.515)	(2.627)	(9.909)	(3.53)
Control High Type	0.155	-0.191	-48.971*	-1.911
	(2.876)	(4.95)	(27.457)	(2.516)
Treated Low Type	10.925**	-3.742	-0.48	-3.046
	(4.616)	(5.471)	(7.786)	(3.849)
Control Low Type	5.646	4.32	-11.674**	-6.125***
	(3.719)	(7.758)	(5.948)	(0.973)
ALL	3.473	2.22	-7.697	-3.46**
	(2.243)	(3.113)	(6.809)	(1.413)

		Sad		
Treated High Type	1.554	-2.995	-12.259**	0.433
	(1.525)	(3.534)	(5.334)	(1.348)
Control High Type	2.028	0.33	-1.377	0.38
	(2.551)	(1.576)	(5.374)	(0.76)
Treated Low Type	0.901	-7.846*	6.681	-1.467
	(2.628)	(4.458)	(5.896)	(1.788)
Control Low Type	0.463	0.995	0.962	1.899
	(3.29)	(10.826)	(7.047)	(1.369)
ALL	1.256	-1.747	-3.005	0.61
	(1.174)	(3.424)	(3.372)	(0.706)
		Surprised		
Treated High Type	-0.325	1.145	-0.555	1.104
	(1.147)	(1.484)	(5.861)	(1.368)
Control High Type	-4.568***	-0.291	1.704	-0.185
	(1.387)	(1.069)	(2.817)	(1.092)
Treated Low Type	1.865	2.109	0.208	1.102
	(1.673)	(2.852)	(1.873)	(1.278)
Control Low Type	3.747	0.658	2.228	0.617
	(4.278)	(4.518)	(4.494)	(1.397)
ALL	-0.728	0.701	0.744	0.676
	(0.905)	(1.375)	(1.914)	(0.638)
		Scared		
Treated High Type	-4.095	-3.989	-12.899**	3.532
	(3.62)	(4.186)	(5.906)	(8.136)
Control High Type	7.556**	5.042**	-5.457	-0.432
	(3.732)	(2.065)	(8.976)	(2.777)
Treated Low Type	-0.361	-5.403	14.078**	3.431**
	(1.698)	(9.013)	(7.027)	(1.709)
Control Low Type	-0.575	16.406	-9.066	5.125
	(5.308)	(12.208)	(7.422)	(4.234)
ALL	0.14	6.185	-4.788	3.018*
	(1.508)	(5.597)	(4.621)	(1.716)
		Disgusted		
Treated High Type	-1.893	-1.084	2.833	-1.657
	(1.616)	(18.894)	(8.771)	(3.004)
Control High Type	5.044	4.266**	33.937**	-5.773
	(3.551)	(1.666)	(14.833)	(4.372)
Treated Low Type	-19.164*	2.835	69.366	0.712
	(10.98)	(4.587)	(44.4)	(3.353)
Control Low Type	0.417	-21.734*	8.807	-3.132**
	(6.048)	(11.43)	(47.624)	(1.56)
ALL	-1.319	-0.896	23.535*	-2.782**
	(2.434)	(3.156)	(12.284)	(1.38)

	Arousal			
Treated High Type	2.658	-0.092	15.628	-0.016
	(3.539)	(3.544)	(23.111)	(3.425)
Control High Type	0.15	-4.35	18.939	2.568
	(4.33)	(4.631)	(15.275)	(7.552)
Treated Low Type	-4.16	13.843	-0.384	2.617
	(9.832)	(8.699)	(9.49)	(2.966)
Control Low Type	5.969	-22.341**	5.806	-2.953
	(7.619)	(10.186)	(10.124)	(2.808)
ALL	1.975	-3.036	9.971	0.46
	(2.694)	(3.698)	(7.479)	(1.89)

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Estimated effects of change in mean emotion from "Info Own" to "Info Others". The first 4 rows in each panel are based on estimates in Tables 2.C.1 to 2.C.9. Estimates for ALL based on Tables 2.C.10 to 2.C.18. All estimates based on random effect regression with robust standard errors clustered on individual level in parentheses.

While there has been no significant treatment effect on the expression of scared and disgusted, several estimates for certain subgroup - variant combinations show significant effects of these emotion on part 2 productivity.

Arousal is the one measure that appeared to be most strongly affected by the treatment in high type subjects. Coefficients for the effect of an increase in arousal on part 2 productivity, however, are positive as well as negative and, with one exception, not statistically significant.

All in all, no clear picture emerges concerning the effect of the different emotion on productivity. But it seems like the effect of emotion on productivity could be context dependent as was seen with regard to the effect of getting happy on productivity.

2.5 Discussion

Overall, the experiments are characterized by a remarkable lack of results. Based on difference-in-difference estimates, the only statistically significant treatment effect with regard to productivity can be reported for high type subjects in the "Start Easy" variant. One potential explanation could be that participants did not perceive the treatment as unfair. However, in an open question at the end of the "Start Hard Wage" experiment, 22 out of 48 treated high type subjects stated that the difference in wages was unfair. What is more, in the same experiment, due to the wage difference in the second part of the real effort task, treated low type participants earned 15.50 EUR at the median whereas treated high type participants earned 5 EUR. Therefore, fairness concerns that aim at equalizing monetary payoff cannot directly explain the lack of adjustments in effort.

In terms of emotion, several arguments can be made for why there might be a lack of facial expression of emotions in response of the treatment. One might be that participants in the experiments were just not moved emotionally. However, the comments in the questionnaire seem to indicate that people felt treated unfairly. Also, anecdotal evidence from the laboratory suggests that people actually got angry. In our opinion, there are three main reasons why no robust treatment effect in terms of emotion was found in the data. First, the treatment was delivered in written form, i.e. participants had to read and understand the information that was given to them. It is our understanding, that the involvement of a more cognitive process might reduce the spontaneous facial expression of emotion. In comparison, tests of the software conducted by the authors outside the lab showed that reactions to various video clips were a lot stronger. Therefore, the communication of information in a form that reduces the involvement of cognitive processes might have facilitated the measurement of a treatment effect in terms of emotion. Second, while it is known when the emotional episode triggered by the treatment could have started the earliest, its actual start and end are not known to the authors. The lack of treatment effects in the facial expression of emotion could therefore be due to a focus on the wrong time span in the analysis. Third, alternative choices for the time emotions are analyzed are not promising as this approach suffers from an open methodological question: Of all the information a constant stream of facial expression provides, which are the relevant facial expressions associated with a stimulus?

The last question appears to be a crucial one. While the Facereader software appears to be at least as good as humans in recognizing facial expressions in pictures (see Lewinski et al., 2014), the interpretation of the resulting data from videos lacks the human ability to tell apart noise and actual information conveyed through facial expressions. In other words, we belief that humans have learned to filter the constant stream of facial expressions they see and interpret the ones they perceive as being related to a certain stimulus. In our opinion, further research is necessary to determine which measures of the recorded emotion correspond most closely to participants emotional episode in the experiment. While we have analyzed certain moments such as mean and median of the emotion distribution over a period of time and compared those to the same moments over a time span we deem neutral, others measures might be superior.

2.6 Conclusion

This paper studies the effect of disadvantageous and preferential treatment of workers on effort as well as the mediating role of emotion in real effort experiments. We show that disadvantaged participants reduce their effort when the disadvantage comes in terms of increased own workload at a constant wage. However, this results is not robust with regard to treatment variations in which a comparison group receives a decreased work load or the treatment comes in terms of wage changes instead of altered tasks. No robust effect of the information on being (dis)advantaged can be reported.

Appendix

2.A Productivity Response

Table 2.A.1: Productivity Response to the Treatment

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.467	0.059	-0.133	0.400*
	(0.585)	(0.242)	(0.713)	(0.212)
High Type	6.927***	2.807***	9.063***	2.650***
	(0.854)	(0.383)	(0.864)	(0.268)
Part 2	0.622	12.590***	1.900***	1.409***
	(0.521)	(0.915)	(0.533)	(0.264)
Treated*High Type	0.471	-0.195	-0.060	-0.034
	(1.073)	(0.398)	(1.438)	(0.329)
Treated*Part 2	-0.081	0.068	-0.400	0.435
	(0.705)	(1.180)	(0.713)	(0.392)
High Type*Part 2	-16.100***	-13.015***	-4.016***	-0.888**
	(0.837)	(0.965)	(1.041)	(0.376)
Treated*High Type*P. 2	-1.295	-0.002	0.516	-0.743
	(1.089)	(1.273)	(1.275)	(0.545)
Time 1st correct	-0.009***	-0.001**	-0.027***	-0.001***
	(0.002)	(0.001)	(0.009)	(0.000)
Female	0.369	-0.169	-1.097	-0.174
	(0.408)	(0.351)	(0.742)	(0.219)
Semester	0.048	0.046***	0.077	0.042
	(0.051)	(0.012)	(0.079)	(0.035)
No Math	-0.465	-0.740*	0.260	-0.196
	(0.456)	(0.384)	(0.807)	(0.322)
(Intercept)	14.107***	3.451***	15.172***	2.445***
	(0.679)	(0.486)	(1.159)	(0.318)
# observations	374	312	322	368
# clusters	187	156	161	184
R^2	0.834	0.747	0.348	0.413

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.1 with robust standard errors clustered on individual level in parentheses.

2.B Emotion Response

Table 2.B.1: Valence Response to Treatment

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.049	0.042	-0.032	0.022
	(0.050)	(0.054)	(0.066)	(0.064)
High Type	0.059	-0.066	-0.045	0.143*
	(0.049)	(0.060)	(0.066)	(0.074)
Treated*High Type	-0.212***	0.004	0.007	-0.044
	(0.069)	(0.074)	(0.085)	(0.086)
Info Others	-0.041	-0.089*	0.007	0.095*
	(0.037)	(0.051)	(0.028)	(0.049)
Treated*Others	-0.078*	0.073	-0.041	-0.066
	(0.047)	(0.062)	(0.041)	(0.056)
High Type*Others	0.020	0.145**	-0.065	-0.103
	(0.063)	(0.058)	(0.049)	(0.063)
Treated*High Type*Others	0.048	-0.120	0.186**	0.112
	(0.081)	(0.083)	(0.073)	(0.079)
Mean Val Task 1	0.390***	0.458***	0.305***	0.566***
	(0.059)	(0.102)	(0.101)	(0.098)
Trait Anger	-0.002	-0.004	-0.005	-0.009**
	(0.004)	(0.004)	(0.005)	(0.005)
Anger Out	0.007	0.012**	-0.006	0.002
	(0.006)	(0.006)	(0.007)	(0.005)
Anger In	-0.002	0.003	0.004	0.004
	(0.004)	(0.005)	(0.004)	(0.004)
Anger Control	0.004	0.003	-0.006	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Time 1st correct2	-0.000*	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.006*	0.004	0.002	-0.004
	(0.004)	(0.004)	(0.003)	(0.006)
No Math	-0.111***	-0.030	-0.091	0.012
	(0.041)	(0.045)	(0.062)	(0.047)
Female	-0.016	0.045	0.051	0.037
	(0.038)	(0.039)	(0.045)	(0.042)
Semester	0.002	-0.005***	-0.006	0.005
	(0.004)	(0.002)	(0.005)	(0.005)
Time	0.004***	0.001	-0.001	-0.002
	(0.001)	(0.002)	(0.002)	(0.002)
(Intercept)	-0.213	-0.413**	0.174	-0.090
	(0.173)	(0.183)	(0.177)	(0.213)
# observations	94,853	80,576	64,821	88,111
# clusters	173	152	154	177
R^2	0.129	0.092	0.142	0.102

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.2 with robust standard errors clustered on individual level in parentheses.

Table 2.B.2: Angry Response to Treatment

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	-0.020	-0.030	0.026	-0.035
	(0.026)	(0.038)	(0.024)	(0.030)
High Type	-0.008	-0.017	0.038	0.014
	(0.028)	(0.041)	(0.027)	(0.032)
Treated*High Type	0.038	-0.010	-0.038	-0.014
	(0.038)	(0.054)	(0.038)	(0.043)
Info Others	-0.001	0.014	-0.002	-0.009
	(0.025)	(0.041)	(0.013)	(0.012)
Treated*Others	0.062**	-0.003	0.021	0.030**
	(0.029)	(0.052)	(0.030)	(0.012)
High Type*Others	-0.005	-0.017	-0.018	0.010
	(0.033)	(0.046)	(0.018)	(0.025)
Treated*High Type*Others	-0.047	0.004	0.019	-0.016
	(0.040)	(0.065)	(0.037)	(0.033)
Mean Angry Task 1	0.472***	0.471***	0.385***	0.672***
	(0.060)	(0.115)	(0.107)	(0.097)
Trait Anger	-0.001	-0.002	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Anger Out	-0.000	-0.001	0.003	-0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
Anger In	0.001	-0.002	-0.004*	-0.002
	(0.002)	(0.003)	(0.002)	(0.002)
Anger Control	-0.001	0.003	0.003*	-0.002
	(0.003)	(0.002)	(0.002)	(0.003)
Time 1st correct2	0.000	-0.000	0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.004*	0.001	0.002*	0.004
	(0.002)	(0.003)	(0.001)	(0.004)
No Math	0.043	-0.026	0.028	0.019
	(0.028)	(0.022)	(0.034)	(0.031)
Female	-0.018	0.005	-0.005	-0.029
	(0.022)	(0.023)	(0.021)	(0.020)
Semester	-0.000	0.003**	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.003)
Time	-0.001	-0.000	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
(Intercept)	0.111	0.051	-0.198**	0.127
	(0.094)	(0.139)	(0.080)	(0.130)
# observations	94,853	80,576	64,821	88,111
# clusters	173	152	154	177
R^2	0.267	0.218	0.282	0.270

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.2 with robust standard errors clustered on individual level in parentheses.

Table 2.B.3: Neutral Response to Treatment

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.035	0.041	-0.086**	-0.045
	(0.032)	(0.033)	(0.042)	(0.039)
High Type	-0.007	-0.001	-0.044	0.010
	(0.032)	(0.033)	(0.042)	(0.043)
Treated*High Type	-0.112***	-0.003	0.073	0.078
	(0.043)	(0.050)	(0.053)	(0.054)
Info Others	0.009	0.020	-0.040*	-0.018
	(0.019)	(0.026)	(0.024)	(0.027)
Treated*Others	-0.063***	0.013	0.056*	0.025
	(0.022)	(0.033)	(0.030)	(0.032)
High Type*Others	-0.054*	-0.007	0.035	-0.024
	(0.032)	(0.031)	(0.033)	(0.034)
Treated*High Type*Others	0.122***	-0.048	-0.046	0.018
	(0.039)	(0.050)	(0.044)	(0.051)
Mean Neutral Task 1	0.486***	0.546***	0.653***	0.454***
	(0.066)	(0.078)	(0.079)	(0.066)
Trait Anger	-0.000	-0.002	0.001	0.005
	(0.003)	(0.003)	(0.004)	(0.003)
Anger Out	-0.004	0.006*	-0.002	-0.006*
	(0.004)	(0.003)	(0.005)	(0.004)
Anger In	0.002	-0.002	0.001	0.002
	(0.002)	(0.003)	(0.003)	(0.003)
Anger Control	-0.003	0.001	-0.003	-0.002
	(0.003)	(0.002)	(0.003)	(0.002)
Time 1st correct2	-0.000***	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.002	-0.000	0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.004)
No Math	-0.017	0.033	0.024	-0.006
	(0.033)	(0.024)	(0.037)	(0.038)
Female	0.007	0.004	0.025	-0.101***
	(0.026)	(0.023)	(0.026)	(0.028)
Semester	0.006*	-0.001	-0.001	-0.002
	(0.003)	(0.001)	(0.003)	(0.004)
Time	0.001	-0.001	0.000	0.000
	(0.001)	(0.002)	(0.001)	(0.001)
(Intercept)	0.305***	-0.002	0.080	0.220
	(0.106)	(0.098)	(0.133)	(0.140)
# observations	94,853	80,576	64,821	88,111
# clusters	173	152	154	177
R^2	0.267	0.278	0.272	0.238

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.2 with robust standard errors clustered on individual level in parentheses.

Table 2.B.4: Happy Response to Treatment

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	-0.003	0.012	-0.013	-0.012
	(0.015)	(0.017)	(0.024)	(0.022)
High Type	0.018	-0.012	-0.008	0.029
	(0.019)	(0.017)	(0.024)	(0.035)
Treated*High Type	-0.029	-0.011	-0.015	-0.041
	(0.021)	(0.020)	(0.026)	(0.035)
Info Others	-0.014	-0.029	-0.016	0.028
	(0.012)	(0.020)	(0.015)	(0.021)
Treated*Others	0.006	0.020	0.002	-0.032
	(0.015)	(0.022)	(0.019)	(0.022)
High Type*Others	0.008	0.032	0.008	-0.022
	(0.026)	(0.021)	(0.017)	(0.032)
Treated*High Type*Others	-0.000	-0.008	0.029	0.062*
	(0.029)	(0.030)	(0.028)	(0.035)
Mean Happy Task 1	0.346	0.652***	0.190	0.734
	(0.244)	(0.222)	(0.168)	(0.559)
Trait Anger	0.000	-0.001	0.000	-0.002
	(0.001)	(0.001)	(0.002)	(0.003)
Anger Out	0.001	0.003	0.001	0.002
	(0.001)	(0.002)	(0.003)	(0.002)
Anger In	-0.002*	0.002	-0.001	0.000
	(0.001)	(0.002)	(0.001)	(0.002)
Anger Control	0.003	-0.001	-0.001	0.000
	(0.002)	(0.001)	(0.001)	(0.001)
Time 1st correct2	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.001	0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.002)
No Math	-0.017*	-0.006	-0.015	-0.013
	(0.010)	(0.009)	(0.010)	(0.023)
Female	0.000	-0.011	-0.009	0.020
	(0.011)	(0.010)	(0.011)	(0.019)
Semester	-0.001	-0.000	0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Time	0.001*	0.000	0.000	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)
(Intercept)	-0.021	0.021	0.119**	0.028
	(0.067)	(0.041)	(0.058)	(0.072)
# observations	94,853	80,576	64,821	88,111
# clusters	173	152	154	177
R^2	0.030	0.068	0.019	0.051

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.2 with robust standard errors clustered on individual level in parentheses.

Table 2.B.5: Sad Response to Treatment

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	-0.051	-0.021	-0.033	0.006
	(0.038)	(0.035)	(0.054)	(0.050)
High Type	-0.018	0.075*	-0.038	-0.108**
	(0.044)	(0.044)	(0.057)	(0.052)
Treated*High Type	0.165***	-0.012	0.033	-0.022
	(0.058)	(0.049)	(0.072)	(0.066)
Info Others	0.029	0.013	-0.025	-0.030
	(0.025)	(0.024)	(0.018)	(0.036)
Treated*Others	0.046	-0.032	0.049	0.002
	(0.031)	(0.033)	(0.033)	(0.039)
High Type*Others	-0.029	-0.075*	0.048	0.044
	(0.045)	(0.039)	(0.033)	(0.041)
Treated*High Type*Others	-0.019	0.100**	-0.131**	-0.019
	(0.058)	(0.050)	(0.053)	(0.054)
Mean Sad Task 1	0.395***	0.886***	0.456**	0.672***
	(0.095)	(0.125)	(0.193)	(0.158)
Trait Anger	-0.001	0.004	0.003	0.005
	(0.003)	(0.003)	(0.004)	(0.004)
Anger Out	-0.004	-0.006	0.000	0.002
	(0.005)	(0.004)	(0.005)	(0.005)
Anger In	0.002	0.002	0.003	-0.001
	(0.003)	(0.004)	(0.003)	(0.003)
Anger Control	-0.000	-0.006*	-0.001	0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Time 1st correct2	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.001	-0.006**	-0.006**	0.001
	(0.003)	(0.002)	(0.003)	(0.004)
No Math	0.022	0.037	0.043	-0.023
	(0.039)	(0.034)	(0.052)	(0.034)
Female	0.020	-0.045*	-0.068*	-0.002
	(0.036)	(0.027)	(0.037)	(0.031)
Semester	-0.004	0.002**	0.004	-0.006*
	(0.004)	(0.001)	(0.004)	(0.003)
Time	-0.003***	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
(Intercept)	0.043	0.330**	0.243	0.026
	(0.113)	(0.155)	(0.150)	(0.172)
# observations	94,853	80,576	64,821	88,111
# clusters	173	152	154	177
R^2	0.133	0.157	0.128	0.145

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.2 with robust standard errors clustered on individual level in parentheses.

Table 2.B.6: Surprised Response to Treatment

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	-0.027	-0.066	0.118	0.138**
	(0.064)	(0.068)	(0.073)	(0.065)
High Type	0.023	-0.009	-0.030	0.028
	(0.067)	(0.069)	(0.074)	(0.065)
Treated*High Type	0.036	0.026	-0.022	-0.104
	(0.083)	(0.088)	(0.097)	(0.087)
Info Others	-0.046	-0.054	0.062*	0.049
	(0.036)	(0.066)	(0.037)	(0.034)
Treated*Others	0.057	0.026	-0.092*	-0.015
	(0.047)	(0.073)	(0.052)	(0.047)
High Type*Others	0.136**	0.082	-0.074	-0.005
	(0.053)	(0.085)	(0.054)	(0.041)
Treated*High Type*Others	-0.215***	-0.034	0.118	0.005
	(0.072)	(0.098)	(0.074)	(0.067)
Mean Surprised Task 1	0.474***	0.506***	0.668***	0.575***
	(0.066)	(0.063)	(0.070)	(0.061)
Trait Anger	-0.002	0.001	-0.004	-0.011**
	(0.005)	(0.005)	(0.006)	(0.005)
Anger Out	0.012	0.003	0.003	0.005
	(0.008)	(0.005)	(0.007)	(0.006)
Anger In	-0.005	0.003	0.001	0.003
	(0.005)	(0.005)	(0.005)	(0.005)
Anger Control	0.007	0.004	-0.000	0.005
	(0.005)	(0.004)	(0.005)	(0.004)
Time 1st correct2	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.006	0.003	0.000	-0.009**
	(0.004)	(0.005)	(0.004)	(0.004)
No Math	-0.037	-0.047	-0.073	0.055
	(0.055)	(0.050)	(0.067)	(0.067)
Female	-0.028	0.029	-0.027	0.128***
	(0.050)	(0.042)	(0.050)	(0.045)
Semester	-0.005	-0.003	-0.009*	0.016***
	(0.006)	(0.002)	(0.005)	(0.006)
Time	0.001	0.000	-0.001	-0.003**
	(0.001)	(0.002)	(0.002)	(0.001)
(Intercept)	-0.022	-0.001	0.369	-0.059
	(0.215)	(0.233)	(0.225)	(0.195)
# observations	94,853	80,576	64,821	88,111
# clusters	173	152	154	177
R^2	0.205	0.238	0.360	0.303

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.2 with robust standard errors clustered on individual level in parentheses.

Table 2.B.7: Scared Response to Treatment

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.028	0.011	0.021	-0.018
	(0.028)	(0.025)	(0.019)	(0.014)
High Type	0.007	-0.006	0.025	-0.033**
	(0.023)	(0.025)	(0.021)	(0.014)
Treated*High Type	-0.023	0.025	-0.029	0.027*
	(0.038)	(0.034)	(0.035)	(0.017)
Info Others	-0.002	0.019	0.011	-0.021*
	(0.011)	(0.017)	(0.013)	(0.011)
Treated*Others	-0.006	-0.021	-0.032*	0.008
	(0.025)	(0.021)	(0.018)	(0.018)
High Type*Others	0.022	-0.018	0.019	0.027*
	(0.023)	(0.024)	(0.039)	(0.014)
Treated*High Type*Others	0.020	0.014	-0.005	-0.015
	(0.033)	(0.031)	(0.043)	(0.021)
Mean Scared Task 1	0.491***	0.582***	0.456*	0.203***
	(0.090)	(0.169)	(0.255)	(0.068)
Trait Anger	0.005*	0.003**	0.000	0.001
	(0.003)	(0.002)	(0.002)	(0.001)
Anger Out	-0.003	-0.000	0.003	-0.001
	(0.003)	(0.003)	(0.003)	(0.001)
Anger In	-0.002	-0.000	-0.003	-0.002**
	(0.002)	(0.001)	(0.002)	(0.001)
Anger Control	-0.001	-0.002	0.003*	0.001
	(0.001)	(0.001)	(0.002)	(0.001)
Time 1st correct2	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.002	0.003	-0.000	0.001
	(0.001)	(0.002)	(0.001)	(0.001)
No Math	0.027	-0.023	-0.010	-0.017**
	(0.026)	(0.016)	(0.017)	(0.008)
Female	0.030*	-0.022	0.044***	0.010
	(0.017)	(0.016)	(0.014)	(0.008)
Semester	0.001	-0.000	0.006**	0.000
	(0.002)	(0.001)	(0.003)	(0.001)
Time	-0.001*	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.000)
(Intercept)	-0.040	-0.035	-0.153**	0.027
	(0.088)	(0.118)	(0.060)	(0.034)
# observations	94,853	80,576	64,821	88,111
# clusters	173	152	154	177
R^2	0.223	0.193	0.236	0.066

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.2 with robust standard errors clustered on individual level in parentheses.

Table 2.B.8: Disgusted Response to Treatment

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	-0.024*	-0.019	-0.001	-0.008
	(0.013)	(0.016)	(0.006)	(0.011)
High Type	-0.027*	-0.023	0.009	0.009
	(0.015)	(0.017)	(0.010)	(0.013)
Treated*High Type	0.040**	0.026	0.009	0.020
	(0.018)	(0.020)	(0.021)	(0.017)
Info Others	-0.009	0.004	-0.001	-0.005
	(0.015)	(0.007)	(0.003)	(0.010)
Treated*Others	0.009	0.015	0.000	-0.008
	(0.014)	(0.016)	(0.004)	(0.009)
High Type*Others	-0.000	-0.006	0.016	0.001
	(0.014)	(0.009)	(0.019)	(0.012)
Treated*High Type*Others	-0.023	-0.001	-0.032	-0.006
	(0.017)	(0.015)	(0.024)	(0.016)
Mean Disgusted Task 1	0.291	0.648***	0.281***	1.221***
	(0.182)	(0.144)	(0.070)	(0.249)
Trait Anger	-0.002**	-0.001	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Anger Out	0.000	-0.001	0.001	0.002*
	(0.002)	(0.001)	(0.001)	(0.001)
Anger In	-0.000	-0.002*	-0.001*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Anger Control	-0.002	0.002*	-0.000	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Time 1st correct2	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.001	-0.003**	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.001)
No Math	0.015	0.035	-0.003	-0.002
	(0.012)	(0.025)	(0.007)	(0.013)
Female	-0.009	-0.002	-0.006	-0.009
	(0.009)	(0.015)	(0.006)	(0.007)
Semester	-0.000	0.001**	-0.001	-0.002
	(0.001)	(0.000)	(0.001)	(0.001)
Time	0.001**	-0.000*	0.000	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
(Intercept)	0.149**	0.072	0.045	0.029
	(0.069)	(0.051)	(0.062)	(0.043)
# observations	94,853	80,576	64,821	88,111
# clusters	173	152	154	177
R^2	0.049	0.046	0.056	0.240

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.2 with robust standard errors clustered on individual level in parentheses.

Table 2.B.9: Arousal Response to Treatment

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.003	0.008	0.010	-0.023
	(0.017)	(0.017)	(0.015)	(0.020)
High Type	0.039*	-0.003	0.033*	-0.015
	(0.023)	(0.016)	(0.018)	(0.020)
Treated*High Type	-0.024	-0.018	-0.049**	0.004
	(0.026)	(0.023)	(0.024)	(0.024)
Info Others	0.026*	0.003	-0.018	-0.018
	(0.014)	(0.014)	(0.014)	(0.014)
Treated*Others	-0.019	-0.016	0.005	0.018
	(0.017)	(0.019)	(0.017)	(0.019)
High Type*Others	-0.066***	-0.022	0.013	-0.014
	(0.018)	(0.019)	(0.017)	(0.015)
Treated*High Type*Others	0.071***	0.079***	0.006	0.023
	(0.024)	(0.029)	(0.023)	(0.024)
Mean Arousal Task 1	0.395***	0.601***	0.223***	0.562***
	(0.105)	(0.102)	(0.084)	(0.124)
Trait Anger	-0.000	-0.003**	0.002*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Anger Out	-0.001	0.001	-0.001	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Anger In	-0.001	0.002	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Anger Control	0.001	-0.002**	0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Time 1st correct2	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.000	-0.001	-0.002	0.000
	(0.001)	(0.001)	(0.001)	(0.002)
No Math	0.005	-0.020*	0.002	-0.026
	(0.018)	(0.012)	(0.017)	(0.019)
Female	0.010	0.014	-0.028**	-0.018
	(0.016)	(0.011)	(0.012)	(0.012)
Semester	-0.000	0.002***	0.002	0.001
	(0.002)	(0.000)	(0.002)	(0.002)
Time	-0.001***	-0.001	-0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.001)
(Intercept)	0.171***	0.214***	0.249***	0.255***
	(0.063)	(0.059)	(0.061)	(0.071)
# observations	94,853	80,576	64,821	88,111
# clusters	173	152	154	177
R^2	0.104	0.130	0.071	0.084

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.2 with robust standard errors clustered on individual level in parentheses.

2.C Emotion and Productivity

Table 2.C.1: Effect of Valence on Productivity

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.711	0.056	0.029	0.523**
	(0.680)	(0.300)	(0.819)	(0.242)
Hightype	7.142***	2.757***	9.289***	2.574***
	(1.009)	(0.473)	(0.955)	(0.284)
Part 2	0.708	12.643***	1.906***	1.520***
	(0.572)	(1.066)	(0.631)	(0.312)
Diff Mean Emo	0.783	-0.445	-4.702	-0.847**
	(1.293)	(0.987)	(4.209)	(0.406)
T*H	0.594	-0.031	-0.543	-0.120
	(1.175)	(0.496)	(1.474)	(0.383)
T*P2	0.277	0.225	-0.194	0.360
	(0.757)	(1.317)	(0.789)	(0.449)
H*P2	-16.176***	-13.076***	-3.417***	-0.993**
	(0.943)	(1.120)	(1.135)	(0.426)
T*DME	-0.844	1.334	1.627	1.931*
	(2.199)	(1.387)	(5.085)	(1.016)
H*DME	-5.162	0.130	0.316	0.947
	(4.071)	(2.331)	(4.889)	(0.802)
P2*DME	-0.816	0.040	2.912	-1.333**
	(2.128)	(4.891)	(4.566)	(0.598)
T*H*P2	-1.657	-0.097	-0.559	-0.708
	(1.195)	(1.415)	(1.370)	(0.605)
T*H*DME	6.086	-0.346	8.387	-3.096**
	(4.761)	(2.851)	(6.285)	(1.336)
T*P2*DME	0.248	2.023	0.306	-0.068
	(2.645)	(5.845)	(5.033)	(1.711)
H*P2*DME	3.820	-0.362	0.353	1.213
	(3.671)	(5.264)	(5.700)	(0.927)
T*H*P2*DME	-4.712	0.902	0.719	1.695
	(4.539)	(6.267)	(6.467)	(2.253)
Mean Emo Task 1	-0.243	0.142	-4.940**	-0.014
	(1.624)	(1.309)	(2.116)	(0.476)
Trait Anger	-0.056	-0.020	0.169*	-0.011
	(0.049)	(0.040)	(0.092)	(0.027)
Anger Control	-0.022	0.043	0.075	0.034
	(0.052)	(0.035)	(0.075)	(0.025)
Anger In	-0.027	-0.033	-0.030	-0.001
	(0.055)	(0.050)	(0.089)	(0.027)
Anger Out	-0.096	0.073	-0.069	-0.030
	(0.101)	(0.058)	(0.134)	(0.031)
Time 1st correct	-0.008***	-0.001**	-0.042**	-0.001***
	(0.002)	(0.001)	(0.018)	(0.000)
Female	0.454	-0.173	-1.047	-0.180
	(0.427)	(0.366)	(0.734)	(0.242)
No Math	-0.483	-0.777*	-0.150	0.015
	(0.550)	(0.405)	(0.848)	(0.375)
Semester	0.046	0.047***	0.095	0.100***
	(0.057)	(0.014)	(0.083)	(0.035)
(Intercept)	17.122***	2.266	11.133***	1.835**
	(2.336)	(1.895)	(3.596)	(0.919)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.846	0.750	0.415	0.452

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.3 with robust standard errors clustered on individual level in parentheses.

Table 2.C.2: Effect of Angry on Productivity

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.464	0.108	1.127	0.665**
	(0.726)	(0.308)	(0.857)	(0.260)
Hightype	7.179***	2.828***	9.581***	2.675***
	(1.070)	(0.459)	(0.908)	(0.290)
Part 2	0.754	12.807***	2.029***	1.507***
	(0.585)	(1.016)	(0.621)	(0.318)
Diff Mean Emo	1.390	0.283	-13.102***	-1.558
	(3.512)	(1.122)	(4.820)	(1.594)
T*H	0.786	-0.159	-1.462	-0.275
	(1.307)	(0.517)	(1.425)	(0.393)
T*P2	0.110	0.075	-0.453	0.266
	(0.812)	(1.281)	(0.790)	(0.456)
H*P2	-16.207***	-13.293***	-3.785***	-0.998**
	(0.936)	(1.067)	(1.139)	(0.431)
T*DME	4.456	-1.038	-2.741	-2.430
	(4.355)	(1.872)	(7.232)	(2.471)
H*DME	2.494	-0.856	39.119***	0.711
	(4.238)	(1.793)	(8.126)	(2.264)
P2*DME	2.474	-6.040*	10.958	3.380**
	(4.838)	(3.373)	(8.507)	(1.554)
T*H*P2	-1.525	0.145	0.205	-0.542
	(1.225)	(1.380)	(1.389)	(0.611)
T*H*DME	-4.760	1.427	-25.243**	3.717
	(6.031)	(2.441)	(10.383)	(3.344)
T*P2*DME	0.508	4.827	-14.742	5.064
	(5.802)	(5.649)	(8.967)	(4.438)
H*P2*DME	-5.345	2.973	-31.013**	-5.363**
	(5.571)	(3.748)	(12.643)	(2.457)
T*H*P2*DME	-0.230	-2.767	29.944**	-7.217
	(8.163)	(6.078)	(13.562)	(5.510)
Mean Emo Task 1	-0.992	1.133	5.145**	0.271
	(1.026)	(1.471)	(2.556)	(0.521)
Trait Anger	-0.061	-0.019	0.218**	-0.005
	(0.047)	(0.039)	(0.102)	(0.029)
Anger Control	-0.016	0.044	0.074	0.022
	(0.046)	(0.037)	(0.072)	(0.024)
Anger In	-0.038	-0.022	-0.045	-0.001
	(0.062)	(0.053)	(0.088)	(0.027)
Anger Out	-0.074	0.078	-0.083	-0.053
	(0.082)	(0.060)	(0.125)	(0.033)
Time 1st correct	-0.008***	-0.001**	-0.062***	-0.001***
	(0.002)	(0.001)	(0.013)	(0.000)
Female	0.396	-0.194	-0.467	-0.204
	(0.458)	(0.372)	(0.734)	(0.248)
No Math	-0.450	-0.630	-0.407	-0.026
	(0.500)	(0.400)	(0.890)	(0.396)
Semester	0.059	0.039**	0.076	0.088**
	(0.058)	(0.015)	(0.087)	(0.036)
(Intercept)	17.127***	1.847	12.304***	2.281**
	(2.219)	(1.893)	(3.283)	(0.932)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.845	0.754	0.416	0.450

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.3 with robust standard errors clustered on individual level in parentheses.

Table 2.C.3: Effect of Neutral on Productivity

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.737	-0.012	1.270	0.598**
	(0.662)	(0.294)	(0.836)	(0.231)
Hightype	7.141***	2.803***	9.706***	2.605***
	(1.027)	(0.419)	(1.031)	(0.291)
Part 2	0.723	12.769***	1.914***	1.424***
	(0.568)	(0.997)	(0.621)	(0.305)
Diff Mean Emo	-9.210**	1.102	-0.960	-1.379
	(4.661)	(2.174)	(4.169)	(1.140)
T*H	0.611	0.069	-1.439	-0.181
	(1.253)	(0.458)	(1.506)	(0.382)
T*P2	-0.068	0.019	-0.485	0.436
	(0.792)	(1.267)	(0.824)	(0.441)
H*P2	-16.068***	-13.225***	-3.427***	-0.784*
	(0.924)	(1.046)	(1.120)	(0.430)
T*DME	6.943	-0.003	-9.810	3.802***
	(5.777)	(2.533)	(7.406)	(1.352)
H*DME	9.310	-1.655	-4.176	1.415
	(5.790)	(2.906)	(6.441)	(1.999)
P2*DME	-3.230	-14.504	-0.989	-0.572
	(4.528)	(9.218)	(3.948)	(2.107)
T*H*P2	-1.425	0.196	-0.040	-0.894
	(1.207)	(1.371)	(1.389)	(0.608)
T*H*DME	-5.305	1.722	26.174**	-4.403**
	(7.508)	(3.678)	(12.209)	(2.198)
T*P2*DME	-5.741	17.491*	5.478	-2.041
	(6.274)	(9.913)	(5.856)	(3.175)
H*P2*DME	4.861	16.816*	-6.132	3.344
	(4.999)	(9.353)	(6.690)	(2.991)
T*H*P2*DME	3.295	-19.413*	4.794	-1.537
	(7.969)	(10.371)	(8.843)	(4.462)
Mean Emo Task 1	0.167	0.025	0.349	-0.587
	(1.066)	(0.999)	(2.043)	(0.500)
Trait Anger	-0.065	-0.020	0.250**	-0.005
	(0.043)	(0.041)	(0.106)	(0.028)
Anger Control	-0.040	0.050	0.094	0.022
	(0.047)	(0.038)	(0.077)	(0.025)
Anger In	-0.041	-0.037	-0.072	-0.002
	(0.061)	(0.046)	(0.089)	(0.027)
Anger Out	-0.088	0.080	-0.112	-0.051
	(0.079)	(0.062)	(0.136)	(0.032)
Time 1st correct	-0.008***	-0.001**	-0.049**	-0.001***
	(0.002)	(0.001)	(0.020)	(0.000)
Female	0.419	-0.229	-1.070	-0.214
	(0.431)	(0.371)	(0.759)	(0.243)
No Math	-0.594	-0.605	0.054	0.007
	(0.462)	(0.422)	(0.794)	(0.355)
Semester	0.024	0.042***	0.124	0.094***
	(0.056)	(0.013)	(0.087)	(0.034)
(Intercept)	17.987***	1.928	11.013***	2.539***
	(2.376)	(2.096)	(3.616)	(0.951)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.846	0.757	0.395	0.455

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.3 with robust standard errors clustered on individual level in parentheses.

Table 2.C.4: Effect of Happy on Productivity

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.857	-0.031	0.806	0.673***
	(0.662)	(0.288)	(0.831)	(0.258)
Hightype	7.128***	2.715***	9.591***	2.710***
	(1.076)	(0.430)	(1.015)	(0.289)
Part 2	0.714	12.636***	1.913***	1.515***
	(0.574)	(1.022)	(0.630)	(0.288)
Diff Mean Emo	5.692	4.472**	-7.092	-1.170
	(4.109)	(2.003)	(5.450)	(1.062)
T*H	0.484	-0.030	-0.710	-0.205
	(1.290)	(0.445)	(1.614)	(0.382)
T*P2	0.275	0.235	-0.298	0.256
	(0.754)	(1.290)	(0.801)	(0.465)
H*P2	-16.176***	-13.091***	-3.369***	-1.000**
	(0.952)	(1.071)	(1.095)	(0.407)
T*DME	7.554	-4.345	3.618	4.034
	(7.699)	(2.811)	(8.869)	(3.757)
H*DME	-11.211	-8.995	-1.108	0.441
	(10.512)	(7.331)	(13.441)	(2.365)
P2*DME	-0.045	-0.152	-4.582	-4.955***
	(4.839)	(6.863)	(4.548)	(1.402)
T*H*P2	-1.596	-0.112	-0.336	-0.616
	(1.207)	(1.387)	(1.362)	(0.625)
T*H*DME	5.281	11.866	1.855	-7.611
	(13.636)	(8.093)	(15.598)	(4.803)
T*P2*DME	-2.275	-3.716	7.577	-0.955
	(10.201)	(8.758)	(7.407)	(5.265)
H*P2*DME	5.720	4.485	-36.188	3.773
	(8.292)	(8.669)	(22.607)	(2.406)
T*H*P2*DME	-11.067	3.458	34.829	3.729
	(13.728)	(10.471)	(24.480)	(6.070)
Mean Emo Task 1	13.776	-2.865	-12.529***	-4.751
	(8.574)	(3.871)	(4.078)	(3.438)
Trait Anger	-0.082*	0.004	0.212**	-0.021
	(0.042)	(0.043)	(0.100)	(0.029)
Anger Control	-0.020	0.051	0.107	0.025
	(0.044)	(0.038)	(0.077)	(0.025)
Anger In	-0.028	-0.032	-0.077	0.009
	(0.055)	(0.048)	(0.090)	(0.028)
Anger Out	-0.080	0.049	-0.048	-0.024
	(0.083)	(0.059)	(0.134)	(0.033)
Time 1st correct	-0.008***	-0.001**	-0.047**	-0.001***
	(0.002)	(0.001)	(0.019)	(0.000)
Female	0.259	-0.265	-1.298	-0.221
	(0.464)	(0.361)	(0.800)	(0.235)
No Math	-0.356	-0.753*	0.079	-0.041
	(0.488)	(0.401)	(0.844)	(0.363)
Semester	0.028	0.047***	0.103	0.097***
	(0.054)	(0.013)	(0.093)	(0.035)
(Intercept)	17.484***	1.952	11.014***	1.958**
	(2.215)	(2.001)	(3.804)	(0.948)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.845	0.749	0.400	0.462

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.3 with robust standard errors clustered on individual level in parentheses.

Table 2.C.5: Effect of Sad on Productivity

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.598	0.130	0.526	0.531**
	(0.701)	(0.295)	(0.838)	(0.246)
Hightype	6.996***	2.827***	9.403***	2.595***
	(0.928)	(0.459)	(1.000)	(0.289)
Part 2	0.685	12.615***	1.808***	1.448***
	(0.583)	(1.022)	(0.597)	(0.302)
Diff Mean Emo	-0.605	0.155	11.571***	1.068
	(1.385)	(1.049)	(3.626)	(0.650)
T*H	0.819	-0.204	-0.967	-0.124
	(1.085)	(0.502)	(1.523)	(0.394)
T*P2	0.283	0.159	-0.231	0.400
	(0.773)	(1.293)	(0.773)	(0.455)
H*P2	-16.128***	-13.039***	-3.311***	-0.928**
	(0.935)	(1.079)	(1.114)	(0.423)
T*DME	-0.057	-1.987	-4.619	-1.781
	(3.924)	(1.910)	(6.096)	(1.623)
H*DME	9.309	-0.345	-8.839*	-1.006
	(9.572)	(3.097)	(5.122)	(1.019)
P2*DME	1.069	0.840	-10.609**	0.831
	(3.152)	(10.089)	(4.573)	(1.304)
T*H*P2	-1.674	0.087	-0.508	-0.734
	(1.200)	(1.394)	(1.360)	(0.614)
T*H*DME	-8.004	2.511	-5.053	2.158
	(10.891)	(4.243)	(8.389)	(1.958)
T*P2*DME	0.495	-6.854	10.338*	-1.585
	(4.581)	(11.107)	(5.345)	(2.911)
H*P2*DME	-7.744	-0.320	6.500	-0.512
	(8.387)	(10.272)	(6.038)	(1.545)
T*H*P2*DME	7.093	3.004	-11.549	1.260
	(9.257)	(11.670)	(7.128)	(3.359)
Mean Emo Task 1	2.551	-3.026*	0.906	0.191
	(4.268)	(1.586)	(4.031)	(0.748)
Trait Anger	-0.059	-0.018	0.191*	-0.006
	(0.047)	(0.039)	(0.099)	(0.029)
Anger Control	-0.030	0.045	0.074	0.031
	(0.048)	(0.034)	(0.081)	(0.025)
Anger In	-0.021	-0.045	-0.040	-0.003
	(0.056)	(0.045)	(0.094)	(0.028)
Anger Out	-0.088	0.057	-0.089	-0.041
	(0.083)	(0.061)	(0.150)	(0.031)
Time 1st correct	-0.008***	-0.001**	-0.051***	-0.001***
	(0.002)	(0.001)	(0.017)	(0.000)
Female	0.555	-0.135	-1.225	-0.177
	(0.421)	(0.354)	(0.768)	(0.239)
No Math	-0.477	-0.842**	-0.041	0.039
	(0.530)	(0.381)	(0.785)	(0.377)
Semester	0.032	0.039***	0.095	0.096***
	(0.062)	(0.013)	(0.091)	(0.035)
(Intercept)	17.175***	2.631	12.631***	1.954**
	(2.122)	(1.838)	(3.631)	(0.928)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.846	0.751	0.399	0.445

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.3 with robust standard errors clustered on individual level in parentheses.

Table 2.C.6: Effect of Surprised on Productivity

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.690	0.019	0.511	0.609**
	(0.677)	(0.281)	(0.807)	(0.237)
Hightype	7.336***	2.742***	9.440***	2.598***
	(1.155)	(0.418)	(0.986)	(0.289)
Part 2	0.703	12.714***	1.709***	1.428***
	(0.579)	(0.998)	(0.642)	(0.303)
Diff Mean Emo	4.591	-0.816	-3.618	0.203
	(3.119)	(0.727)	(3.165)	(0.593)
T*H	0.193	0.061	-0.910	-0.142
	(1.399)	(0.452)	(1.466)	(0.383)
T*P2	0.125	0.279	-0.165	0.425
	(0.765)	(1.264)	(0.832)	(0.443)
H*P2	-16.214***	-13.140***	-3.201***	-0.895**
	(1.035)	(1.049)	(1.127)	(0.418)
T*DME	-5.888*	-0.371	4.230	-0.453
	(3.519)	(1.152)	(3.838)	(1.043)
H*DME	-10.760**	1.543	-0.237	-0.247
	(5.377)	(1.149)	(3.882)	(1.023)
P2*DME	-0.843	1.474	5.846*	0.414
	(2.948)	(4.168)	(3.128)	(1.343)
T*H*P2	-1.463	-0.144	-0.382	-0.752
	(1.271)	(1.362)	(1.389)	(0.596)
T*H*DME	11.919**	-1.065	-3.927	0.627
	(5.797)	(1.638)	(6.315)	(1.480)
T*P2*DME	4.005	1.822	-6.251*	0.938
	(3.246)	(5.282)	(3.504)	(1.844)
H*P2*DME	2.445	-2.492	-0.287	-0.555
	(4.242)	(4.259)	(4.074)	(1.733)
T*H*P2*DME	-5.794	1.050	3.689	0.177
	(5.167)	(5.493)	(5.416)	(2.391)
Mean Emo Task 1	-0.054	-0.109	-1.868	0.477
	(0.658)	(0.682)	(1.539)	(0.360)
Trait Anger	-0.073*	-0.018	0.150	-0.006
	(0.044)	(0.039)	(0.099)	(0.028)
Anger Control	-0.002	0.050	0.079	0.027
	(0.046)	(0.036)	(0.075)	(0.024)
Anger In	-0.077	-0.038	-0.024	0.003
	(0.068)	(0.047)	(0.091)	(0.026)
Anger Out	-0.046	0.070	-0.007	-0.044
	(0.069)	(0.062)	(0.138)	(0.033)
Time 1st correct	-0.009***	-0.001**	-0.052***	-0.001***
	(0.002)	(0.001)	(0.019)	(0.000)
Female	0.666*	-0.187	-0.694	-0.264
	(0.401)	(0.364)	(0.780)	(0.261)
No Math	-0.622	-0.680	0.203	0.047
	(0.510)	(0.431)	(0.845)	(0.387)
Semester	0.043	0.044***	0.122	0.093***
	(0.056)	(0.014)	(0.100)	(0.035)
(Intercept)	17.364***	2.147	12.605***	1.865*
	(2.240)	(1.997)	(3.637)	(0.979)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.846	0.750	0.388	0.447

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.3 with robust standard errors clustered on individual level in parentheses.

Table 2.C.7: Effect of Scared on Productivity

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.784	0.098	0.907	0.547**
	(0.710)	(0.289)	(0.791)	(0.267)
Hightype	7.014***	2.881***	9.720***	2.600***
	(1.050)	(0.440)	(1.044)	(0.312)
Part 2	0.675	12.246***	2.077***	1.508***
	(0.585)	(0.850)	(0.603)	(0.316)
Diff Mean Emo	0.995	0.412	2.519	1.320
	(6.727)	(1.741)	(3.965)	(2.072)
T*H	0.667	-0.118	-1.086	-0.145
	(1.293)	(0.484)	(1.506)	(0.406)
T*P2	0.258	0.634	-0.538	0.373
	(0.795)	(1.153)	(0.779)	(0.447)
H*P2	-16.091***	-12.691***	-3.555***	-0.985**
	(0.926)	(0.908)	(1.132)	(0.442)
T*DME	0.029	1.167	15.320***	-2.155
	(6.897)	(2.913)	(5.827)	(2.600)
H*DME	2.102	2.066	-1.333	-2.798
	(7.595)	(3.314)	(7.032)	(4.297)
P2*DME	-1.570	15.995	-11.586	3.805
	(4.112)	(11.089)	(8.761)	(4.379)
T*H*P2	-1.687	-0.459	-0.035	-0.728
	(1.202)	(1.258)	(1.388)	(0.615)
T*H*DME	-7.306	-3.768	-29.027***	2.927
	(8.692)	(3.974)	(8.571)	(6.948)
T*P2*DME	0.185	-22.976	7.823	0.461
	(4.401)	(14.722)	(11.313)	(4.987)
H*P2*DME	6.030	-13.430	4.942	-2.759
	(6.185)	(11.485)	(10.920)	(6.221)
T*H*P2*DME	-4.559	16.546	-1.559	2.731
	(8.308)	(15.348)	(13.429)	(8.391)
Mean Emo Task 1	-1.366	-1.368	4.487*	-0.759
	(1.960)	(1.829)	(2.432)	(0.878)
Trait Anger	-0.071	-0.011	0.209**	-0.004
	(0.047)	(0.038)	(0.097)	(0.028)
Anger Control	-0.028	0.055	0.117	0.026
	(0.047)	(0.040)	(0.079)	(0.025)
Anger In	-0.028	-0.029	-0.062	-0.001
	(0.062)	(0.044)	(0.092)	(0.028)
Anger Out	-0.079	0.070	-0.049	-0.055
	(0.085)	(0.060)	(0.136)	(0.034)
Time 1st correct	-0.008***	-0.001**	-0.048**	-0.001***
	(0.002)	(0.001)	(0.019)	(0.000)
Female	0.374	-0.178	-1.248	-0.183
	(0.434)	(0.382)	(0.783)	(0.241)
No Math	-0.517	-0.558	0.317	0.033
	(0.539)	(0.398)	(0.887)	(0.377)
Semester	0.039	0.037***	0.093	0.094***
	(0.057)	(0.014)	(0.088)	(0.035)
(Intercept)	17.572***	1.629	10.218***	2.300**
	(2.328)	(2.020)	(3.852)	(0.938)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.843	0.765	0.388	0.447

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.3 with robust standard errors clustered on individual level in parentheses.

Table 2.C.8: Effect of Disgusted on Productivity

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.768	0.016	0.658	0.597^{**}
	(0.701)	(0.284)	(0.805)	(0.253)
Hightype	7.081^{***}	2.722^{***}	9.442^{***}	2.655^{***}
	(1.040)	(0.407)	(1.012)	(0.286)
Part 2	0.732	12.670^{***}	1.893^{***}	1.480^{***}
	(0.573)	(0.985)	(0.627)	(0.293)
Diff Mean Emo	-1.512	-2.231	45.560	0.686
	(5.557)	(2.572)	(29.147)	(1.171)
T*H	0.664	0.017	-0.863	-0.212
	(1.287)	(0.444)	(1.526)	(0.388)
T*P2	0.439	0.163	-0.373	0.392
	(0.766)	(1.284)	(0.799)	(0.442)
H*P2	-16.148^{***}	-13.160^{***}	-3.521^{***}	-0.946^{**}
	(0.913)	(1.035)	(1.141)	(0.409)
T*DME	-0.665	1.714	2.107	-0.460
	(17.510)	(3.446)	(47.328)	(3.572)
H*DME	-6.035	1.244	-24.155	-1.798
	(8.522)	(2.810)	(31.369)	(4.043)
P2*DME	1.929	-19.503^{*}	-36.753	-3.818^{**}
	(3.887)	(10.824)	(24.631)	(1.504)
T*H*P2	-1.870	0.083	-0.043	-0.742
	(1.180)	(1.383)	(1.392)	(0.599)
T*H*DME	5.239	-0.644	-23.393	0.577
	(18.786)	(10.655)	(50.441)	(5.601)
T*P2*DME	-18.916^{*}	22.855^{*}	58.452	4.304
	(10.386)	(11.689)	(38.983)	(5.448)
H*P2*DME	10.662	24.755^{**}	49.286^{*}	-0.843
	(7.223)	(10.851)	(25.908)	(4.972)
T*H*P2*DME	7.406	-29.274	-68.271^{*}	-0.306
	(12.197)	(22.502)	(39.851)	(7.682)
Mean Emo Task 1	-5.437^{*}	-0.724	-9.492^{**}	0.697
	(2.810)	(6.312)	(4.542)	(1.674)
Trait Anger	-0.073	-0.028	0.189^{*}	-0.013
	(0.045)	(0.042)	(0.100)	(0.029)
Anger Control	-0.020	0.050	0.105	0.022
	(0.047)	(0.035)	(0.082)	(0.026)
Anger In	-0.038	-0.028	-0.048	0.001
	(0.062)	(0.045)	(0.093)	(0.027)
Anger Out	-0.069	0.069	-0.008	-0.054
	(0.085)	(0.062)	(0.136)	(0.033)
Time 1st correct	-0.008^{***}	-0.001^{**}	-0.053^{***}	-0.001^{***}
	(0.002)	(0.001)	(0.018)	(0.000)
Female	0.342	-0.146	-1.050	-0.222
	(0.441)	(0.370)	(0.774)	(0.242)
No Math	-0.320	-0.525	0.250	0.037
	(0.557)	(0.414)	(0.847)	(0.368)
Semester	0.048	0.046^{***}	0.103	0.091^{**}
	(0.054)	(0.012)	(0.090)	(0.037)
(Intercept)	17.302^{***}	2.160	10.982^{***}	2.455^{**}
	(2.319)	(1.914)	(3.976)	(1.038)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.845	0.752	0.398	0.446

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.3 with robust standard errors clustered on individual level in parentheses.

Table 2.C.9: Effect of Arousal on Productivity

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.921	0.053	0.604	0.557**
	(0.681)	(0.287)	(0.924)	(0.237)
Hightype	7.024***	2.609***	9.321***	2.708***
	(0.887)	(0.428)	(1.103)	(0.317)
Part 2	0.674	12.466***	1.928**	1.407***
	(0.566)	(0.919)	(0.748)	(0.312)
Diff Mean Emo	-1.350	-3.615	6.370	-1.400
	(5.507)	(2.378)	(8.603)	(1.748)
T*H	0.504	0.071	-0.579	-0.212
	(1.119)	(0.460)	(1.681)	(0.407)
T*P2	0.086	0.939	-0.357	0.458
	(0.766)	(1.287)	(0.895)	(0.446)
H*P2	-16.056***	-12.971***	-3.459***	-0.800
	(0.885)	(0.971)	(1.202)	(0.504)
T*DME	14.736	2.015	-7.392	2.749
	(10.400)	(3.030)	(12.203)	(2.203)
H*DME	1.012	0.991	4.984	1.678
	(9.597)	(3.257)	(15.473)	(4.272)
P2*DME	7.319	-18.726*	-0.563	-1.553
	(6.800)	(10.380)	(8.929)	(2.927)
T*H*P2	-1.555	-0.660	-0.124	-0.890
	(1.163)	(1.398)	(1.444)	(0.662)
T*H*DME	-10.675	1.088	0.925	-4.026
	(13.435)	(4.161)	(21.923)	(5.032)
T*P2*DME	-24.865**	34.169**	1.202	2.821
	(11.562)	(13.771)	(10.381)	(4.659)
H*P2*DME	-6.831	17.000	8.149	3.844
	(9.512)	(11.089)	(17.123)	(6.948)
T*H*P2*DME	23.312	-33.014**	1.955	-4.127
	(14.586)	(14.568)	(24.198)	(8.313)
Mean Emo Task 1	1.015	-0.245	6.811	4.123*
	(3.294)	(3.656)	(10.591)	(2.456)
Trait Anger	-0.060	0.002	0.185*	-0.006
	(0.046)	(0.037)	(0.101)	(0.029)
Anger Control	-0.020	0.053	0.100	0.023
	(0.049)	(0.036)	(0.079)	(0.026)
Anger In	-0.031	-0.050	-0.047	-0.001
	(0.058)	(0.050)	(0.090)	(0.027)
Anger Out	-0.086	0.072	-0.075	-0.052
	(0.089)	(0.062)	(0.133)	(0.035)
Time 1st correct	-0.008***	-0.002**	-0.049**	-0.001***
	(0.002)	(0.001)	(0.019)	(0.000)
Female	0.357	-0.093	-1.017	-0.204
	(0.474)	(0.368)	(0.789)	(0.241)
No Math	-0.467	-0.776*	0.379	-0.004
	(0.505)	(0.419)	(0.853)	(0.334)
Semester	0.047	0.042***	0.075	0.088***
	(0.057)	(0.013)	(0.094)	(0.033)
(Intercept)	16.908***	1.898	9.969**	1.206
	(2.320)	(2.059)	(4.299)	(1.208)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.845	0.764	0.382	0.450

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.3 with robust standard errors clustered on individual level in parentheses.

Table 2.C.10: Effect of Valence on Productivity (ALL)

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.686	0.008	0.237	0.574**
	(0.681)	(0.293)	(0.809)	(0.245)
High Type	7.085***	2.694***	9.366***	2.600***
	(0.982)	(0.464)	(0.971)	(0.281)
Part 2	0.716	12.758***	1.898***	1.457***
	(0.569)	(0.984)	(0.616)	(0.300)
Diff Mean Emotion	-0.956	0.178	-0.203	-0.310
	(1.203)	(0.595)	(1.709)	(0.329)
Treated*High Type	0.666	0.033	-0.463	-0.151
	(1.142)	(0.476)	(1.482)	(0.382)
Treated*Part 2	0.290	0.119	-0.169	0.415
	(0.752)	(1.239)	(0.784)	(0.435)
High Type*Part 2	-16.126***	-13.256***	-3.407***	-0.941**
	(0.924)	(1.042)	(1.117)	(0.419)
Part 2*Diff Mean Emotion	0.245	1.171	3.607**	-0.329
	(1.223)	(1.661)	(1.474)	(0.589)
Treated*High Type*Part 2	-1.724	0.104	-0.554	-0.743
	(1.168)	(1.334)	(1.374)	(0.601)
Mean Emotion Task 1	-0.308	-0.173	-5.007**	-0.072
	(1.688)	(1.282)	(2.034)	(0.479)
Trait Anger	-0.056	-0.020	0.175*	-0.007
	(0.050)	(0.039)	(0.091)	(0.027)
Anger Control	-0.023	0.047	0.069	0.024
	(0.051)	(0.035)	(0.074)	(0.024)
Anger In	-0.030	-0.031	-0.039	0.001
	(0.057)	(0.048)	(0.089)	(0.027)
Anger Out	-0.085	0.076	-0.088	-0.049
	(0.096)	(0.057)	(0.130)	(0.030)
Time 1st correct	-0.008***	-0.001**	-0.042**	-0.001***
	(0.002)	(0.001)	(0.018)	(0.000)
Female	0.426	-0.185	-0.869	-0.199
	(0.417)	(0.369)	(0.724)	(0.236)
No Math	-0.512	-0.705*	-0.200	0.013
	(0.549)	(0.393)	(0.879)	(0.368)
Semester	0.050	0.044***	0.082	0.095***
	(0.057)	(0.013)	(0.085)	(0.035)
(Intercept)	17.010***	2.096	11.494***	2.204**
	(2.295)	(1.890)	(3.597)	(0.897)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.844	0.749	0.398	0.441

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.4 with robust standard errors clustered on individual level in parentheses.

Table 2.C.11: Effect of Angry on Productivity (ALL)

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.523	0.077	0.780	0.616^{**}
	(0.691)	(0.308)	(0.802)	(0.249)
High Type	7.111^{***}	2.797^{***}	9.313^{***}	2.664^{***}
	(1.034)	(0.462)	(0.975)	(0.282)
Part 2	0.702	12.724^{***}	1.899^{***}	1.412^{***}
	(0.569)	(0.986)	(0.628)	(0.304)
Diff Mean Emotion	3.671^{***}	-0.184	-2.300	-0.706
	(1.327)	(0.558)	(3.679)	(0.882)
Treated*High Type	0.758	-0.118	-0.842	-0.207
	(1.255)	(0.511)	(1.467)	(0.382)
Treated*Part 2	0.331	0.147	-0.320	0.469
	(0.767)	(1.255)	(0.791)	(0.447)
High Type*Part 2	-16.120^{***}	-13.210^{***}	-3.488^{***}	-0.892^{**}
	(0.909)	(1.043)	(1.117)	(0.413)
Part 2*Diff Mean Emotion	-0.731	-3.052^{*}	-5.241	-1.118
	(2.005)	(1.705)	(3.429)	(1.899)
Treated*High Type*Part 2	-1.765	0.039	-0.091	-0.790
	(1.157)	(1.353)	(1.371)	(0.595)
Mean Emotion Task 1	-0.725	0.973	5.049^{*}	0.186
	(1.001)	(1.450)	(2.739)	(0.491)
Trait Anger	-0.057	-0.023	0.185^{*}	-0.004
	(0.046)	(0.039)	(0.096)	(0.028)
Anger Control	-0.014	0.040	0.071	0.023
	(0.045)	(0.037)	(0.071)	(0.024)
Anger In	-0.040	-0.022	-0.045	-0.001
	(0.060)	(0.050)	(0.088)	(0.027)
Anger Out	-0.082	0.078	-0.049	-0.054
	(0.081)	(0.057)	(0.126)	(0.033)
Time 1st correct	-0.008^{***}	-0.001^{**}	-0.052^{***}	-0.001^{***}
	(0.002)	(0.001)	(0.016)	(0.000)
Female	0.355	-0.192	-0.628	-0.193
	(0.442)	(0.364)	(0.736)	(0.244)
No Math	-0.452	-0.673^{*}	-0.020	-0.034
	(0.500)	(0.398)	(0.821)	(0.386)
Semester	0.055	0.041^{***}	0.091	0.090^{**}
	(0.056)	(0.014)	(0.088)	(0.035)
(Intercept)	17.171^{***}	2.050	11.806^{***}	2.233^{**}
	(2.192)	(1.900)	(3.524)	(0.899)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.844	0.752	0.391	0.441

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.4 with robust standard errors clustered on individual level in parentheses.

Table 2.C.12: Effect of Neutral on Productivity (ALL)

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.742	0.022	0.959	0.590^{**}
	(0.679)	(0.287)	(0.820)	(0.237)
High Type	7.066^{***}	2.741^{***}	9.650^{***}	2.620^{***}
	(1.012)	(0.419)	(1.029)	(0.289)
Part 2	0.718	12.641^{***}	1.929^{***}	1.433^{***}
	(0.565)	(0.992)	(0.619)	(0.299)
Diff Mean Emotion	-1.293	0.763	-0.875	-0.149
	(1.960)	(0.771)	(2.994)	(0.557)
Treated*High Type	0.695	0.035	-1.180	-0.166
	(1.249)	(0.454)	(1.564)	(0.377)
Treated*Part 2	0.229	0.255	-0.347	0.435
	(0.757)	(1.248)	(0.804)	(0.437)
High Type*Part 2	-16.173^{***}	-13.087^{***}	-3.457^{***}	-0.906^{**}
	(0.916)	(1.041)	(1.128)	(0.415)
Part 2*Diff Mean Emotion	-1.373	-0.218	-0.445	-0.164
	(1.955)	(2.188)	(2.248)	(1.220)
Treated*High Type*Part 2	-1.609	-0.064	-0.180	-0.777
	(1.190)	(1.342)	(1.388)	(0.593)
Mean Emotion Task 1	0.254	-0.260	-0.079	-0.733
	(1.023)	(0.949)	(1.989)	(0.481)
Trait Anger	-0.061	-0.021	0.197^{*}	-0.004
	(0.044)	(0.039)	(0.102)	(0.028)
Anger Control	-0.027	0.048	0.082	0.027
	(0.045)	(0.035)	(0.075)	(0.024)
Anger In	-0.023	-0.036	-0.048	-0.000
	(0.061)	(0.045)	(0.089)	(0.026)
Anger Out	-0.097	0.075	-0.048	-0.050
	(0.080)	(0.061)	(0.138)	(0.033)
Time 1st correct	-0.008^{***}	-0.001^{**}	-0.050^{**}	-0.001^{***}
	(0.002)	(0.001)	(0.020)	(0.000)
Female	0.389	-0.198	-1.003	-0.211
	(0.443)	(0.360)	(0.755)	(0.238)
No Math	-0.524	-0.687^{*}	0.132	-0.003
	(0.492)	(0.384)	(0.869)	(0.367)
Semester	0.038	0.044^{***}	0.093	0.094^{***}
	(0.058)	(0.012)	(0.091)	(0.035)
(Intercept)	17.303^{***}	2.247	11.538^{***}	2.305^{**}
	(2.330)	(1.905)	(3.669)	(0.901)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.844	0.748	0.369	0.442

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.4 with robust standard errors clustered on individual level in parentheses.

Table 2.C.13: Effect of Happy on Productivity (ALL)

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.828	0.016	0.777	0.585**
	(0.679)	(0.278)	(0.787)	(0.247)
High Type	7.132***	2.750***	9.541***	2.683***
	(1.082)	(0.428)	(1.001)	(0.286)
Part 2	0.720	12.655***	1.920***	1.471***
	(0.569)	(0.993)	(0.619)	(0.289)
Diff Mean Emotion	2.950	1.328	-4.317	-1.240
	(3.886)	(1.666)	(3.079)	(0.938)
Treated*High Type	0.563	-0.069	-0.559	-0.170
	(1.278)	(0.439)	(1.576)	(0.376)
Treated*Part 2	0.282	0.238	-0.407	0.361
	(0.754)	(1.256)	(0.790)	(0.434)
High Type*Part 2	-16.131***	-13.104***	-3.444***	-0.972**
	(0.941)	(1.043)	(1.110)	(0.408)
Part 2*Diff Mean Emotion	0.523	0.892	-3.380	-2.220*
	(3.337)	(2.683)	(4.949)	(1.264)
Treated*High Type*Part 2	-1.721	-0.057	-0.049	-0.630
	(1.177)	(1.355)	(1.385)	(0.602)
Mean Emotion Task 1	15.767*	-4.450	-13.313***	-5.160
	(8.520)	(3.221)	(4.455)	(3.495)
Trait Anger	-0.065	-0.007	0.220**	-0.015
	(0.044)	(0.042)	(0.098)	(0.028)
Anger Control	-0.014	0.044	0.098	0.021
	(0.043)	(0.036)	(0.076)	(0.024)
Anger In	-0.043	-0.036	-0.068	0.006
	(0.056)	(0.046)	(0.089)	(0.027)
Anger Out	-0.078	0.058	-0.070	-0.036
	(0.083)	(0.060)	(0.131)	(0.030)
Time 1st correct	-0.008***	-0.001**	-0.047**	-0.001***
	(0.002)	(0.001)	(0.018)	(0.000)
Female	0.316	-0.194	-1.249	-0.231
	(0.417)	(0.359)	(0.790)	(0.236)
No Math	-0.536	-0.768*	0.080	-0.071
	(0.492)	(0.396)	(0.826)	(0.356)
Semester	0.038	0.044***	0.090	0.093***
	(0.054)	(0.012)	(0.091)	(0.035)
(Intercept)	17.082***	2.292	11.261***	2.229**
	(2.127)	(1.895)	(3.711)	(0.890)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.844	0.748	0.382	0.454

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.4 with robust standard errors clustered on individual level in parentheses.

Table 2.C.14: Effect of Sad on Productivity (ALL)

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.594	0.119	0.804	0.579**
	(0.692)	(0.293)	(0.832)	(0.240)
High Type	6.991***	2.752***	9.620***	2.613***
	(0.896)	(0.429)	(1.018)	(0.284)
Part 2	0.721	12.681***	1.885***	1.440***
	(0.572)	(0.981)	(0.598)	(0.298)
Diff Mean Emotion	1.504	-0.251	1.461	0.347
	(1.451)	(1.053)	(2.692)	(0.437)
Treated*High Type	0.887	-0.135	-0.974	-0.165
	(1.027)	(0.471)	(1.520)	(0.384)
Treated*Part 2	0.284	0.179	-0.154	0.436
	(0.752)	(1.250)	(0.782)	(0.437)
High Type*Part 2	-16.127***	-13.196***	-3.385***	-0.917**
	(0.933)	(1.034)	(1.106)	(0.417)
Part 2*Diff Mean Emotion	-0.248	-1.496	-4.465**	0.263
	(1.811)	(3.230)	(1.804)	(0.716)
Treated*High Type*Part 2	-1.725	0.118	-0.557	-0.773
	(1.168)	(1.367)	(1.366)	(0.594)
Mean Emotion Task 1	2.812	-2.312	0.257	0.209
	(4.661)	(1.741)	(3.911)	(0.781)
Trait Anger	-0.057	-0.016	0.194**	-0.005
	(0.048)	(0.038)	(0.098)	(0.028)
Anger Control	-0.021	0.051	0.087	0.025
	(0.046)	(0.034)	(0.078)	(0.024)
Anger In	-0.029	-0.044	-0.046	-0.001
	(0.059)	(0.045)	(0.091)	(0.027)
Anger Out	-0.087	0.065	-0.045	-0.050
	(0.084)	(0.060)	(0.145)	(0.031)
Time 1st correct	-0.008***	-0.001**	-0.049**	-0.001***
	(0.002)	(0.001)	(0.020)	(0.000)
Female	0.477	-0.141	-0.988	-0.205
	(0.415)	(0.354)	(0.763)	(0.233)
No Math	-0.475	-0.717*	0.125	0.002
	(0.519)	(0.384)	(0.839)	(0.374)
Semester	0.027	0.044***	0.094	0.093***
	(0.064)	(0.012)	(0.090)	(0.035)
(Intercept)	17.006***	2.312	11.296***	2.206**
	(2.029)	(1.888)	(3.743)	(0.895)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.844	0.749	0.376	0.439

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.4 with robust standard errors clustered on individual level in parentheses.

Table 2.C.15: Effect of Surprised on Productivity (ALL)

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.828	0.020	0.409	0.607**
	(0.710)	(0.276)	(0.794)	(0.239)
High Type	7.225***	2.741***	9.505***	2.603***
	(1.098)	(0.416)	(0.985)	(0.285)
Part 2	0.729	12.692***	1.823***	1.424***
	(0.571)	(0.983)	(0.607)	(0.299)
Diff Mean Emotion	-1.846	-0.341	-2.238	0.023
	(1.474)	(0.397)	(1.646)	(0.383)
Treated*High Type	0.329	0.030	-0.800	-0.147
	(1.390)	(0.445)	(1.495)	(0.379)
Treated*Part 2	0.210	0.230	-0.088	0.438
	(0.759)	(1.251)	(0.812)	(0.434)
High Type*Part 2	-16.207***	-13.162***	-3.332***	-0.890**
	(0.957)	(1.039)	(1.107)	(0.413)
Part 2*Diff Mean Emotion	1.118	1.042	2.982**	0.653
	(1.356)	(1.328)	(1.322)	(0.581)
Treated*High Type*Part 2	-1.551	-0.033	-0.441	-0.771
	(1.242)	(1.351)	(1.374)	(0.591)
Mean Emotion Task 1	-0.239	-0.133	-1.862	0.456
	(0.713)	(0.650)	(1.524)	(0.339)
Trait Anger	-0.061	-0.018	0.150	-0.006
	(0.045)	(0.039)	(0.098)	(0.027)
Anger Control	-0.017	0.050	0.079	0.026
	(0.046)	(0.035)	(0.073)	(0.024)
Anger In	-0.046	-0.037	-0.026	0.003
	(0.066)	(0.046)	(0.088)	(0.026)
Anger Out	-0.057	0.071	-0.012	-0.046
	(0.072)	(0.060)	(0.134)	(0.033)
Time 1st correct	-0.008***	-0.001**	-0.052***	-0.001***
	(0.002)	(0.001)	(0.019)	(0.000)
Female	0.399	-0.192	-0.690	-0.258
	(0.418)	(0.359)	(0.775)	(0.249)
No Math	-0.454	-0.671*	0.219	0.017
	(0.514)	(0.399)	(0.849)	(0.371)
Semester	0.050	0.044***	0.118	0.094***
	(0.058)	(0.013)	(0.097)	(0.035)
(Intercept)	17.024***	2.147	12.627***	1.908**
	(2.294)	(1.959)	(3.593)	(0.959)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.845	0.748	0.381	0.444

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.4 with robust standard errors clustered on individual level in parentheses.

Table 2.C.16: Effect of Scared on Productivity (ALL)

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.731	0.047	0.812	0.593**
	(0.679)	(0.283)	(0.791)	(0.247)
High Type	7.041***	2.857***	9.685***	2.643***
	(1.025)	(0.437)	(1.026)	(0.288)
Part 2	0.706	12.512***	1.999***	1.499***
	(0.569)	(0.901)	(0.599)	(0.299)
Diff Mean Emotion	0.474	1.003	0.165	-0.339
	(1.872)	(1.077)	(3.976)	(1.240)
Treated*High Type	0.645	-0.031	-1.118	-0.180
	(1.251)	(0.469)	(1.500)	(0.388)
Treated*Part 2	0.278	0.384	-0.469	0.378
	(0.757)	(1.196)	(0.770)	(0.432)
High Type*Part 2	-16.110***	-12.954***	-3.491***	-0.998**
	(0.912)	(0.954)	(1.108)	(0.427)
Part 2*Diff Mean Emotion	-0.334	5.182	-4.953	3.358*
	(1.668)	(5.252)	(3.680)	(1.839)
Treated*High Type*Part 2	-1.716	-0.164	-0.057	-0.708
	(1.171)	(1.312)	(1.355)	(0.596)
Mean Emotion Task 1	-1.461	-0.624	4.014	-1.227*
	(1.959)	(1.831)	(2.889)	(0.725)
Trait Anger	-0.062	-0.017	0.189**	-0.007
	(0.045)	(0.039)	(0.095)	(0.028)
Anger Control	-0.019	0.037	0.101	0.024
	(0.046)	(0.037)	(0.078)	(0.024)
Anger In	-0.037	-0.028	-0.051	0.001
	(0.060)	(0.046)	(0.091)	(0.027)
Anger Out	-0.071	0.064	-0.027	-0.055
	(0.084)	(0.059)	(0.132)	(0.034)
Time 1st correct	-0.008***	-0.001**	-0.048**	-0.001***
	(0.002)	(0.001)	(0.019)	(0.000)
Female	0.380	-0.219	-1.129	-0.186
	(0.435)	(0.367)	(0.755)	(0.237)
No Math	-0.469	-0.723*	-0.064	0.039
	(0.529)	(0.405)	(0.860)	(0.373)
Semester	0.047	0.044***	0.088	0.096***
	(0.056)	(0.012)	(0.090)	(0.035)
(Intercept)	17.110***	2.256	10.741***	2.321**
	(2.275)	(1.878)	(3.855)	(0.923)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.844	0.752	0.374	0.444

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.4 with robust standard errors clustered on individual level in parentheses.

Table 2.C.17: Effect of Disgusted on Productivity (ALL)

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.784	0.046	0.754	0.581**
	(0.688)	(0.276)	(0.799)	(0.250)
High Type	7.110***	2.732***	9.504***	2.642***
	(1.029)	(0.409)	(0.999)	(0.281)
Part 2	0.729	12.639***	1.953***	1.467***
	(0.567)	(0.990)	(0.623)	(0.291)
Diff Mean Emotion	-2.905	-0.939	14.964*	-0.099
	(2.177)	(0.899)	(8.681)	(1.067)
Treated*High Type	0.645	-0.003	-0.874	-0.194
	(1.265)	(0.439)	(1.514)	(0.382)
Treated*Part 2	0.256	0.249	-0.404	0.382
	(0.753)	(1.257)	(0.791)	(0.433)
High Type*Part 2	-16.135***	-13.087***	-3.550***	-0.933**
	(0.908)	(1.034)	(1.125)	(0.407)
Part 2*Diff Mean Emotion	1.587	0.043	8.571	-2.683**
	(1.974)	(3.209)	(5.512)	(1.196)
Treated*High Type*Part 2	-1.699	-0.052	-0.024	-0.739
	(1.167)	(1.354)	(1.382)	(0.591)
Mean Emotion Task 1	-5.421*	-2.266	-7.441*	0.717
	(2.866)	(5.952)	(4.110)	(1.553)
Trait Anger	-0.069	-0.016	0.176*	-0.012
	(0.044)	(0.039)	(0.096)	(0.028)
Anger Control	-0.020	0.051	0.070	0.023
	(0.046)	(0.035)	(0.078)	(0.024)
Anger In	-0.035	-0.036	-0.041	-0.001
	(0.061)	(0.045)	(0.092)	(0.027)
Anger Out	-0.069	0.075	-0.042	-0.052
	(0.084)	(0.061)	(0.135)	(0.033)
Time 1st correct	-0.008***	-0.001**	-0.049**	-0.001***
	(0.002)	(0.001)	(0.019)	(0.000)
Female	0.371	-0.182	-1.190	-0.210
	(0.430)	(0.360)	(0.780)	(0.237)
No Math	-0.362	-0.662*	0.236	0.028
	(0.532)	(0.395)	(0.835)	(0.365)
Semester	0.044	0.045***	0.095	0.091**
	(0.056)	(0.012)	(0.089)	(0.036)
(Intercept)	17.136***	1.977	12.311***	2.404***
	(2.226)	(1.884)	(3.772)	(0.926)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.844	0.747	0.386	0.443

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.4 with robust standard errors clustered on individual level in parentheses.

Table 2.C.18: Effect of Arousal on Productivity (ALL)

	Start Easy	Start Hard	Start Easy Wage	Start Hard Wage
Treated	0.791	0.012	0.648	0.533^{**}
	(0.687)	(0.274)	(0.822)	(0.239)
High Type	7.186^{***}	2.680^{***}	9.399^{***}	2.646^{***}
	(0.995)	(0.417)	(1.020)	(0.284)
Part 2	0.719	12.623^{***}	2.053^{***}	1.446^{***}
	(0.570)	(0.974)	(0.658)	(0.303)
Diff Mean Emotion	2.832	-1.314	5.314	-0.107
	(3.030)	(1.056)	(4.619)	(1.146)
Treated*High Type	0.475	0.140	-0.676	-0.176
	(1.221)	(0.456)	(1.581)	(0.384)
Treated*Part 2	0.269	0.208	-0.465	0.420
	(0.757)	(1.282)	(0.816)	(0.435)
High Type*Part 2	-16.164^{***}	-13.128^{***}	-3.584^{***}	-0.895^{**}
	(0.912)	(1.054)	(1.142)	(0.415)
Part 2*Diff Mean Emotion	-0.857	-1.722	4.657	0.568
	(3.557)	(3.464)	(5.596)	(1.752)
Treated*High Type*Part 2	-1.674	0.120	-0.040	-0.792
	(1.169)	(1.485)	(1.392)	(0.599)
Mean Emotion Task 1	1.277	0.410	5.983	3.958^{*}
	(3.313)	(3.658)	(9.452)	(2.371)
Trait Anger	-0.063	-0.012	0.200^{**}	-0.002
	(0.044)	(0.039)	(0.100)	(0.028)
Anger Control	-0.018	0.054	0.101	0.027
	(0.047)	(0.036)	(0.078)	(0.025)
Anger In	-0.034	-0.037	-0.058	-0.003
	(0.059)	(0.045)	(0.089)	(0.027)
Anger Out	-0.081	0.080	-0.076	-0.053
	(0.083)	(0.062)	(0.136)	(0.035)
Time 1st correct	-0.008^{***}	-0.001^{**}	-0.047^{**}	-0.001^{***}
	(0.002)	(0.001)	(0.019)	(0.000)
Female	0.425	-0.188	-1.089	-0.219
	(0.436)	(0.361)	(0.771)	(0.246)
No Math	-0.505	-0.698^{*}	0.326	0.005
	(0.513)	(0.391)	(0.850)	(0.353)
Semester	0.046	0.044^{***}	0.089	0.091^{***}
	(0.056)	(0.013)	(0.092)	(0.035)
(Intercept)	16.782^{***}	1.677	9.843^{**}	1.123
	(2.246)	(2.134)	(4.182)	(1.192)
# observations	324	292	284	330
# clusters	162	146	142	175
R^2	0.844	0.748	0.376	0.444

Notes. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Random effect regression based on Equation 2.4 with robust standard errors clustered on individual level in parentheses.

2.D Instructions & Consent Form

The following two pages contain translations of the instruction the participants receive[27] and a consent form for being filmed.

[27] The instructions given here were used in the "Start Easy" variant. In all other variants, only the description of task or piece rate changed according to the treatment.

Welcome to our experiment!

During the experiment, you are not allowed to use electronic devices or communicate with other participants. Please only use the software and functions intended to be used in the experiment. Please do not talk to other participants. In case you have a question, please raise your hand. We will come to your desk and answer your question in private. Please do not ask questions aloud. In case your question is relevant for all participants, we will repeat it and answer it for all participants. Should you violate those rules, we have to exclude you from the experiment and payment.

If your read these instructions carefully you can earn a significant amount of money. The payoff you receive during the experiment will be payed out in cash at the end of the experiment. Everything in this experiment will happen exactly as described in this instruction. In addition, we assure you that your data is only used in anonymized form.

Basic structure of the experiment

The experiment consists of two parts. In part 1, you will solve tasks. For every correctly solved task you will receive 0.50 EUR. This part lasts 30 minutes and your performance in this part of the experiment can affect part 2 of the experiment. Afterwards, you will receive additional information on part 2 of the experiment.

In part 2 of the experiment you can again earn money by solving tasks. This part as well takes 30 minutes. Your payoff is fixed after the second part of the experiment. Subsequently, we ask you to fill out a questionnaire.

Task in Part 1

The task in part 1 of the experiment consists of typing a string of numbers and letters without error. This string will be displayed on the computer screen. You will receive money for every correctly typed strings. In the 30 min you have to your disposal, you can solve as many task as you wish. The time you have left is displayed on screen. For every correct task, you will receive 0.50 EUR.

Payoff

You will earn money in this experiment that will be payed in cash at the end of the experiment. In addition to what you earn during the experiment, you will receive 5 EUR for showing up.

Thank you for participating!

Consent form

You are about to sign up for an experiment which will be recorded using video cameras. The footage will be handled strictly confidential and is used for purely scientific reason. No personal information or data will be given to third parties. In our research, we stringently follow all guidelines of the states data protection law. All employees that handle your data in scientific analysis are bound to follow §8 Berliner Datenschutsgesetz (BerlDSG).

All work places have webcams installed to record actions and reactions of participants. The video data that will collected during the experiment will be saved on a secured storing device at the WZB and deleted after 10 years. The duration and way of storage are in accordance with recommendation 7 of the DFG for self-monitoring of science.

I have read and understood the consent form and agree that the my video footage can be used for scientific purposes. The recorded video will not be published.

Date, signature

Chapter 3

Solidarity, Responsibility and In-group Bias*

3.1 Introduction

> "Solidarity means a willingness to help people in need who are similar to oneself but victims of outside influences such as unforeseen illness, natural catastrophes, etc." (Selten & Ockenfels, 1998, p. 518)

Widespread solidarity is a form of *insurance* without explicit contracts. All types of insurance, however, suffer from the problems of moral hazard and adverse selection. Therefore, whenever possible, insurance differentiates between customers from different risk classes and rules out payment in cases of gross negligence. Higher risk groups receive less coverage or have to pay higher fees. It is then a natural question to ask whether voluntary solidarity also differentiates between risk groups and/or people who consciously decide to take higher or lower risks. Indeed, when assuming that a relevant part of the population cares, in contrast to insurance companies, not only about monetary payoffs, we may very well expect that there is a difference between solidarity and insurance.

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One the one hand, it can be imagined that those who are ready to take high risks may be held partly *responsible* if they fail – and therefore receive smaller solidarity transfers – just as would be the case with insurance contracts. This view was confirmed experimentally where it was shown that "there was (...) broad support for the view that individuals should be held responsible for their choice (...)."(Cappelen et al., 2010, p. 440). Note that this responsibility argument requires discrimination of beneficiaries but no differentiation based on characteristics of the benefactors.

On the other hand, it is possible that behavior depends on characteristics of the benefactor as well. It could, for example, be the case that benefactors who also have taken risks (and succeeded) may be more sympathetic to fellow risk-takers. It is easier for them to put themselves in their shoes than in those of "scaredy-cats", and vice versa. Another potential reason for differentiation is the existence of a behavioral norm or fairness standard which requires treating people who took the same action differently from people who took different actions (see e.g. Cappelen et al., 2013). A third potential reason for differently behaving benefactors is the formation of group-identity feelings with the consequence of in-group favoritism which is supported by a vast amount of literature that started with Tajfel (1970). The consequences of these last three lines of reasoning for observed behavior are very similar and it is therefore hard to distinguish between them[2]. As our experiment is not aimed at differentiating between these motives, we will not take a stand on which one offers the more plausible explanation. Outside our experiment differentiating between a fairness standard based on actions taken and pure discrimination based on belonging to a group is certainly important, though. While most people see differences in outcomes as just which are due to different actions, this is not true if discrimination is based on group belonging with the definition of that group not being related to the action in question.

Holding people responsible for their decisions (as suggested by the first argument) and favoritism of individuals with the same risk-choice suggest different types of solidarity behavior between people who decide to take a higher risk and those who do not. According to the responsibility argument, people in need would receive less help if they chose the more risky option. For individuals who favor others who made the same choice, however, lucky risk takers show more support for needy risk takers than towards needy risk averters and vice versa. It is the aim of this paper to experimentally evaluated whether favoritism of people with similar choice of risk can overcome the motive to hold

[2]In fact, they might be intertwined in the sense that in-group favoritism based on shared identity works partly because it is easier to put oneself in the shoes of others to which one feels closer connected.

people responsible for their decision.

In the next section, closely related literature is presented that gives support to the different potential underlying motives. The experiment is described in Section 3.3 and in Section 3.4, following Cappelen et al. (2013), a theory of redistribution is suggested. This order is preferable because hypotheses can be formulated with respect to the specific experimental conditions. In Section 3.5 the experimental results are presented and a variant of the Cappelen et al. (2013) social utility function is estimated. Section 3.6 concludes.

3.2 Literature

The question, what people should be held responsible for, has been answered in various ways. These normative answers consist (among others) of the two extremes "libertarianism" and "strict egalitarianism", i.e. the notion that individuals should be held responsible for all factors that lead to some distribution of resources or that they should not be held responsible at all. In between, there is a wide variety of other concepts according to which individuals should be held responsible for some factors that determine distribution of income but not for others. One prominent concept that relates to the fair distribution of income is equality of opportunity. In the sense of Rawls (1971), equality of fair opportunity implies that individuals should not only formally have the same opportunities but that individuals of same ability should have the same effective chance. The libertarian Robert Nozick stresses in particular this role of ability and other endowments. He illustrates this principle by asking the question of whether it would be just to reallocate resources and spend those on cosmetic surgery and intelligence training for men that were less lucky in the natural lottery than himself with the aim of leveling the playing field in competing for women (Nozick, 1974, p. 237). Nozick concludes that these inequalities in opportunity do not justify reallocating resources. Roemer (1995) adds a for our experiment important differentiation between brute bad luck and option bad luck in the determination of outcomes. Brute bad luck refers to bad outcomes that result from unavoidable risks, whereas option bad luck occurs in case risk was consciously taken but resulted in a bad outcome. This differentiation leads him to conclude that "Even under an equal-opportunity view, we might well decide that society should insure its citizens against brute bad luck, but not against option bad luck. Under an equal outcome view, society must insure its citizens against bad luck of any kind, whether the consequence of voluntary gambles or not."(Roemer, 1995).

In a dictator game with preceding production phase, Cappelen et al. (2010) investigate empirically what factors individuals are held responsible for, i.e.

whether participants are compensated for a lack of equal opportunity or even for an unequal distribution of outcomes in case equality of opportunity existed. Although their participants can be classified according to various normative concepts, about 80 percent of the subjects support the view that individuals should be held responsible for factors that are within their control (the choice of working time in their experiment) whereas more than 70 percent of their experimental subjects reject the view that people should be held responsible for factors that are beyond their control (the price per unit produced as chosen by the experimenter). This result is also related to the accountability principle as stated in Konow (2000) which requires that someones entitlement varies in direct proportion to his or her discretionary variables.

However, it was not analyzed whether fairness views were conditional on characteristics of the benefactor. This question received attention in a different study (Cappelen et al., 2013) where experimental subjects first had a binary choice of either a risk-less income or a lottery ticket. Then the ex-post aggregate income of two randomly matched subjects could be redistributed by one of them or by a spectator without own interests. Cappelen et al. (2013) find that the redistribution behavior of their subjects can be explained by subjects having one of three types of social utility functions which are based on either one of two unconditional fairness norms or on a conditional fairness norm. The latter implies discrimination of in-group and out-group subjects where the risk-takers form one group and the risk-averters the other and was estimated to be present with about 30 percent of the subjects. We will come back to their model in Section 3.4.

Another mechanism which would lead to outcomes being conditional on characteristics of the benefactor is the formation of group-identity, a mechanism first studied in the experiments by Tajfel (1970). In these experiments, he shows that even for groups defined by rather meaningless categories there is significant in-group/out-group discrimination. Tajfel (1970) thereby spurred a huge literature in the social sciences on social identity (a good overview is given in Chen and Li (2009)). Within economics, the role of identity was introduced by Akerlof and Kranton (2000) which incorporated identity into an economic model (see also Akerlof & Kranton, 2002, 2005). Following their seminal work, identity received increased attention in the experimental economics literature and has been studied in the lab as well as in the field. In the lab, Chen and Li (2009) show that there is more altruism and less envy as well as more positive reciprocity and less negative reciprocity between members of the same group than between members of different groups and Charness, Rigotti, and Rustichini (2007) find that the effect of group-membership depends positively on salience of the group. Outside the lab, Bernhard, Fehr, and Fischbacher (2006) found in-group favoritism with regard to norm enforcement in a natural field experiment in Papua New Guinea. What is more, in-group/out-group differentiation can not only robustly be observed in experiments, it can also be derived from various social categories as Ben-Ner, McCall, Stephane, and Wang (2009) show. Their experimental subjects not only give more in dictator games if the receiver has similar religious or political views, favors the same sports team or looks alike, they are also more eager to share an office with people similar in those categories or to commute with them. Notably, only one category did not cause in-group/out-group differentiation and this was gender.

An interesting question is why there is discrimination at all? Here, different evolutionary arguments can be made. According to Eaton, Eswaran, and Oxoby (2011), the origin of group formation and in-group favoritism is the hunter-gatherer society in which mankind for 99 percent of its existence has lived. In a group where food is at least partly shared, risk averse individuals' utility maximization requires supporting other risk averse individuals who help to create a steady stream of food. On the other hand, if someone is risk-prone he also would like his group to be risk-prone. In addition, Costard et al. (2013) show in an evolutionary setting that a strategy purely differentiating between in-group and out-group typically outperforms other more elaborate strategies that build on reputation and indirect reciprocity.

Solidarity, as studied in experimental economics, has mainly been investigated in the framework of the Dictator game and the Solidarity game. In the original Solidarity game of Selten and Ockenfels (1998), the three members of a group are each endowed with DM 10 with 2/3 probability and with DM 0 with 1/3 probability. In the cases where there are winners (who got DM 10) and losers (who got nothing), the winner(s) can give an arbitrary amount of their endowment to the loser(s). Further experiments investigate the impact of the strategy method (Büchner, Coricelli, & Greiner, 2007), the influence of culture (Ockenfels & Weimann, 1999), or are concerned with the identification of different types of behavior (Bolle, Breitmoser, Heimel, & Vogel, 2012). We may regard the Dictator game as a two-person solidarity game although it is rarely discussed under this aspect. It seems that in the dictator game roles (rich and poor) are "given" while in the Solidarity game the random mechanism which determines incomes (winners and losers) is emphasized. In addition, for some purposes the three-player design has advantages. If the only winner of a group determines his transfer to two *different* losers then we can directly see whether and how they are treated differently.

An experiment closely related to ours is Trhal and Radermacher (2009), where the original Solidarity game (Solidarity Treatment ST) was conducted as well as another experiment, called Risk Treatment RT. In RT each of the three participants of a solidarity group had to choose between lottery C: "EUR 10 with certainty" or lottery R: "EUR 0 with Prob=0.5, EUR 10 with Prob=0.4, EUR 60 with Prob=0.1". In RT, only winners of EUR 10 were allowed to compensate losers. All subjects played both treatments, half of them in the order (ST, RT) and half of them in the opposite order, each time in a newly formed group. Trhal and Radermacher (2009) find that subjects in RT who voluntarily took risks and failed, receive less compensation than subjects in ST who could not avoid risks.

Our paper will analyze giving behavior in a variant of the Solidarity game which is close to the Trhal and Radermacher (2009) design. However we will show that solidarity transfers are heavily influenced by in-group favoritism with group-membership defined by the level of risk-taking.

3.3 The Experiment

The experiment took place at the European-University Viadrina in Frankfurt (Oder), Germany, in 2009. 237 students from the faculties Economics and Business, Law, and Cultural Sciences participated in the experiment. They were invited via email and distributed into two sessions. Each session lasted about one hour. The subjects were placed in a large lecture hall as in written exams, i.e. with so much space between them that the six experimenters could prevent communication. All participants received a show-up fee of EUR 3. The experiment started by giving the participants an instruction form and a first decision form[3]. The instruction form explained that an initial income would be created by one of two random processes (lottery tickets) between which they could choose.

- *Random process A*: With probability 2/3 you "win" EUR 10, with probability 1/3 you receive EUR 0.
- *Random process B*: With probability 1/3 you "win" EUR 20, with probability 2/3 you receive EUR 0.

They were further told that they would be matched with two other (anonymous) people in the room to form a group of three. If their group consisted only of "winners" or "losers" (who receive EUR 0) then the game would end. If it consisted of winners and losers, the winner(s) could transfer arbitrary parts of their prize to the loser(s). After receiving this general information the subjects chose A or B (knowing that there would be a phase with voluntary transfers). They also reported their expectation about the frequencies of A- and B-choices.

[3]The English translation of both forms are reproduced in the Appendix.

Then they had to draw an A- or B-envelope (according to their decision) from a box[4]. By opening the envelope they found a new decision form.

First they were informed that they were winners or losers. We deviated from a complete strategy method because the winners had to decide among five further conditions (see below). An additional fundamental conditionality ("if you are a winner") might have restricted the perceived relevance of decisions too much. Because of the same reason we restricted the number of conditions to five. In the following, those who have chosen A and lost (received EUR 0) are called A-losers, the others A-winners. B-losers and B-winners are defined respectively. The winners decided on their transfers for the different possible loser structures and reported their expectations about the other winner's transfers in the one-loser case. Losers decided on transfers "they would have made if they had been winners". The losers' hypothetical decisions served mainly to keep them busy and not to disturb the winners and are not subject of the following analysis. The participants were told that all payments would be carried out according to the random matching of participants. They could collect their money later from a person not involved in the experiment (after reporting their subject number and their self-chosen pseudonym).

We required the winners to make conditional transfer decisions in five different situations:

1. How much would you give to a single A-loser? [5]
2. How much would you give to a single B-loser?
3. How much would you give to each of two A-losers?
4. How much would you give to each of two B-losers?
5. If there is one A-loser and one B-loser, how much would you give to the A-loser and how much to the B-loser?

In the end they were asked to write a short comment on their decisions. In addition, they reported their gender, faculty, semester and age.

3.4 Solidarity Theory

In this section, we introduce an extension of the two-person social utility function of Cappelen et al. (2013) to apply it to our experimental setting. In particular, we make it a three-person social utility function to match our three-player

[4]Within about five minutes, six experimenters with boxes distributed the new decision forms.

[5]I.e. there are two winners and one loser. In order not to introduce further ramifications of the hypothetical decisions, the type of the other winner is not revealed.

experimental set-up. For the case where there is one winner and two losers, it takes the following form

$$V_i = \gamma y_i - \beta_i \frac{(y_j - F^{k(j)})^2}{2X} - \beta_i \frac{(y_h - F^{k(h)})^2}{2X} \tag{3.1}$$

Here, y_i is the income which winner i reserves for himself and y_j and y_h are the losers' incomes, i.e. i's transfers to them. $X = y_i + y_j + y_h$ is i's prize (EUR 10 or EUR 20). γ is a general and β_i is an individual positive parameter and $F^{k(j)}$ is a reference income for player j. In Cappelen et al. (2013), three different versions of this reference income are considered. First, winner i could have a preference for equalizing income ex post, unconditional of actions taken. She would therefore exhibit an ex post standard "equality of income" which corresponds to a reference income $F^{EP} = X/3$ for both players j and h. Second, winner i might prefer not to equalize income ex post, again unconditional of actions taken. As all players start out in the same situation, this can be called a preference for "equality of opportunity" and implies a reference income of $F^{EA} = 0$ for both players j and h[6]. Third, reference income might depend on actions taken, so being conditional on past actions, in contrast to the previous two cases. Cappelen et al. (2013) analyze the case where the ex post standard "equality of income" is applied to individuals who took the same action as the benefactor and the ex ante standard "equality of opportunity" is applied to individuals who took a different action. Cappelen et al. (2013) prefer to interpret these different reference incomes as "ex ante", "ex post" and "conditional" fairness standards. However, as discussed above, alternative interpretations are possible, especially with regard to the "conditional" fairness standard.

The social utility function yields the following forecast for the transfer of winner i to loser j

$$\frac{y_j}{X} = \max\left(0, \frac{F^{k(j)}}{X} - \frac{\gamma}{\beta_i}\right) \tag{3.2}$$

and correspondingly for loser h. Based on our three-player setting and the different reference incomes, $F^{k(j)}/X = 0$ or $F^{k(j)}/X = 1/3$. This implies (ceteris paribus) independence of transfers from the question whether the winner is an A-winner or B-winner. Transfers would, however, differ for losers of a

[6]To be precise, the reference income $F^{EA} = 0$ is consistent with equality of opportunity in the sense of Rawls (1971) only if it can be taken for granted that all experimental subjects have the same ability in evaluating the lotteries between which the chose. If it would be the case that all participants have the same basic intellectual ability but some have no training in mathematics and therefore no understanding of what probabilities are there would be no equality of fair opportunity as Rawls (1971) sees it. For Nozick (1974), in contrast, no entitlement would follow even for those subjects that lack knowledge of probabilities. As all our experimental subjects are university students which received mathematical training at least in high school, we assume that equality of opportunity is satisfied also in the sense of Rawls (1971).

certain type if the winner's preferences reveal in-group favoritism.

If there is one loser j and a second winner h, then the utility function becomes

$$V_i = \gamma y_i - \beta_i \frac{(E_i[y_i] - F^{k(j)})^2}{2E_i[X]} - \beta_i \frac{(E_i[y_i] - F^{k(h)})^2}{2E_i[X]} \tag{3.3}$$

whereas $E_i[y_j] = t_i + E_i[t_h]$ is the loser's expected income after i's transfer t_i and h's expected transfer $E_i[t_h]$. The "ex post" standard is defined as $F^{EP} = E_i[X]/3$ with

$$E_i[X] = i\text{'s lottery prize } + 20\frac{1+\alpha_i}{3+\alpha_i} \tag{3.4}$$

with α_i being i's expected share of A-players[7]. i's maximization of equation (3.3) yields

$$\frac{t_i}{E_i[X]} = \max\left(0, \frac{F^{k(j)}}{E_i[X]} - \frac{E_i[t_h]}{E_i[X]} - \frac{\gamma}{\beta_i}\right) \tag{3.5}$$

While the expected shares of A-players are nearly the same in our experiment (66 percent and 63 percent for A- and B-winners) the expectations $E_i[t_h]$ are rather different. A-winners expect on average transfers of EUR 1.82 and B-winners EUR 2.85. The difference is highly significant ($p < 10^{-7}$ in a two-sided Mann-Whitney U-test). In relation to $E_i[X]$, however, we find

$$\text{average } \frac{E_i[t_h]}{E_i[X]} = 0.0997 \text{ for A-winners and } 0.0992 \text{ for B-winners.} \tag{3.6}$$

Therefore we expect the same result as in the two-loser case, however in terms of shares of $E_i[X]$: If there are no further differences between A- and B-players then they should transfer the same shares of $E_i[X]$.

Using the elicited expectations of the other winner's transfer in this way implies the hypothesis that, first, subjects develop expectations, and then they decide on transfers based on these expectations. Alternatively, we can assume that the two winners determine the Bayesian equilibrium of the public good game they play. (In the case of interdependent utility functions the income of the loser is a public good or bad for the winners.) We could not use the expectations as in (3.4) if the winners determine the transfers first (with whatever rationale) and then determine their expectations on the basis of their own transfers. For a discussion of this problem see Selten and Ockenfels (1998).

Based on the theoretical framework, we expect the experimental results to feature the following characteristics. First, in-group transfers as share of the prize won will be independent of the winners' lottery choice. Second, out-group transfers as share of the prize will be independent of the winners' lottery choice.

[7]The conditional probability that the only other winner is an A-winner is $(4\alpha_i/9)/(4\alpha_i/9 + (1-\alpha_i)/9) = 4\alpha_i/(1+3\alpha_i)$.

Third, in-group transfers will be higher than out-group transfers[8].

3.5 Results

230 of the 237 participants delivered completely filled questionnaires. Among these there were 60 percent female students. The faculties were represented with 60 percent economics and business students, 15 percent law students and 26 percent cultural science students. It is remarkable that only 47 percent of our subjects chose the less risky A and 53 percent the more risky B lottery. On the first glance this seems to be an astonishingly high number of risk seekers. In Cappelen et al. (2013), for example, 90 percent of the subjects preferred a riskless income to a risky lottery with the same expectation value. Note, however, that this difference is at least partly caused by the well-known certainty effect (see also Cohen & Jaffray, 1988). Another reason for so many risk seekers might be that they are somewhat insured by the expected solidarity transfers[9]. It is also interesting to note that the average expectations of the frequencies of B-choices are 35 percent which is less ($p = 0.07$ in a chi square test) than the real choices of B but which is still large if one expects most people to be risk averse.

We observe a gender effect with regard to the lottery choice. While 62% of male participants chose the more risky lottery B this was only true for 47% of female participants. In the end, we had 73 A-winners and 35 B-winners, which are the basis of the following analysis. Only 5 of these 108 decision makers (4 percent) did not collect their money. The average transfers of A-winners to A-losers, EUR 1.27 in the one-loser case and EUR 1.13 in the two-loser case, are close to those in treatment ST of Trhal and Radermacher (2009).

3.5.1 Aggregate Results

The average relative amounts which losers receive are presented in Table 3.1 and Table 3.2. In the one winner/two losers case the expected group income $E_i[X]$ is equal to the prize which the only winner receives. The simple result is strong discrimination: In-group transfers are between 10.8 percent and 12.7 percent of the winner's prize. Out-group transfers are between 7.0 percent and 8.8 percent of the winner's prize. The hypothesis of in-group/out-group differentiation is therefore strongly supported (only for the comparison of in-group and out-group transfers for B-players in the case of two winners measured

[8]In the case of two winners, these statements apply to the share of the expected prize won by both winners.

[9]In a follow-up investigation by Lübbe and Bolle (2011), however, it is shown that moral hazard does not play a significant role for the choice of B.

Table 3.1: Relative transfers from winners to losers in the two winners case.

Type	Transfers to receiver of type A: in % of prize	A: in % of $E_i[X]$	B: in % of prize	B: in % of $E_i[X]$	N
A-player	12.7* (11.3)	6.7* (5.9)	7.2 (9.3)	3.8 (4.9)	73
B-player	8.8 (11.4)	6.4 (8.3)	11.3* (11.8)	8.3+ (8.6)	35

*(+) indicate that transfer is significantly larger than corresponding transfer to losers of the other type (Wilcoxon matched pairs rank test with $p < 0.01$ ($p = 0.06$)). Standard deviations in brackets.

Table 3.2: Relative transfers from winners to losers in the one winner case.

Type	Transfers to receivers of type: Losers of same type A	Losers of same type B	Losers of mixed types A	Losers of mixed types B	N
A-player	11.3* (9.1)	6.8 (7.9)	12.4* (9.9)	7.0 (8.1)	73
B-player	7.1 (7.7)	9.6* (10.8)	7.0 (8.1)	10.8* (12.0)	35

* indicate that transfer is significantly larger than corresponding transfer to losers of the other type (Wilcoxon matched pairs rank test with $p < 0.01$). Standard deviations in brackets.

as shares of $E_i[X]$ the level of significance is lower). Interestingly, although there is a gender effect with regard to lottery choice, there is no gender effect with regard to in-group/out-group differentiation, i.e. also female participants transfered more to losers that chose the same lottery. Also the other hypotheses, namely that in-group transfers and out-group transfers do not differ between A-winners and B-winners, is supported as no statistical differences ($p < 0.05$) can be found. These finding continue to hold when controlling for individual attributes such as gender, field of study or age of the experimental subjects in an OLS-regression. For details, we refer to Appendix 3.B.

3.5.2 Structural Modeling

Finally, we want to investigate the model of Section 3.4 and the question of whether A- and B-players have different preferences beyond their risk attitudes with a random utility approach (McFadden, 1973; McKelvey & Palfrey, 1995). We concentrate on the one winner/two losers case because we want to avoid the discussion mentioned in Section 3.4 about the nature of the expectation formation in the two winners/one loser case.

We add a random term ϵ_i to the utility function (3.1), i.e.

$$V_i^k(y_j, y_k) = \gamma(X - y_y - y_h) - \beta_i \frac{(y_j - F^{k(j)})^2}{2X} - \beta_i \frac{(y_h - F^{k(h)})^2}{2X} + \epsilon_i \quad (3.7)$$

and assume that ϵ_i is i.i.d. extreme value. The individual choice probabilities then have a logit form. Following Cappelen et al. (2013) we assume $\log \beta_i$ to be normally distributed with $\log \beta_i \sim \mathcal{N}(\mu, \sigma)$[10].

The winners' transfers could not be more than half of their prize and only 8 of the 432 transfers were not a multiple of 50 Eurocent. Thus we choose finite sets of possible transfers (in Euro) to one loser, namely $T = T_A = \{0, 0.5, 1.0, \dots, 5.0\}$ for A-winners and $T = T_B = \{0, 0.5, 1.0, \dots, 10.0\}$ for B-winners. The eight deviating values are set equal to the closest element of the finite sets.

i's decision under the three conditions $y_j = y_h = \tau_{i \to AA}, y_j = y_h = \tau_{i \to BB}$, and $y_j = \tau_{i \to AB}, y_h = \tau_{i \to BA}$ lead to utilities $V^k(AA)$, $V^k(BB)$ and $V^k(AB)$, whereas $\tau_{i \to jh}$ is the transfer of winner i to losers j and h. The expected likelihood of these three decisions is

$$L_i^k = L_i^k(\tau_{i \to AA}, \tau_{i \to BB}, \tau_{i \to AB}, \tau_{i \to BA}, \gamma, \mu, \sigma) = \int_0^\infty \frac{\exp(V_i^k(AA)) \exp(V_i^k(BB)) \exp(V_i^k(AB))}{\sum_{x \in T} \exp(V_i^k(y, y)) \sum_{x \in T} \exp(V_i^k(y, y)) \sum_{(y,z) \in T * T} \exp(V_i^k(y, z))} dF(\mu, \sigma) \quad (3.8)$$

where F is the lognormal distribution. We assume the standard $k = EA$ to be present in the population with a share of λ^{EA} , standard EP with λ^{EP} and standard CE with $\lambda^{CE} = 1 - \lambda^{EA} - \lambda^{EP}$. Then the average likelihood of the three decisions is

$$L_i = \lambda^{EA} L_i^{EA} + \lambda^{EP} L_i^{EP} + \left(1 - \lambda^{EA} - \lambda^{EP}\right) L_i^{CE} \quad (3.9)$$

In order to find out whether A- and B-players are different we estimate the parameters $(\gamma, \mu, \sigma, \lambda^{EA}, \lambda^{EP})$ for A- and B-players separately and jointly (see Table 3.3). The reduction of the log-likelihood score of 16.0 after adopting separate estimates surpasses the critical limit described by the BIC and the AIC criteria. The improvement is also highly significant in a likelihood ratio test ($p = 4 \cdot 10^{-5}$). The differences between A- and B-players are mainly the different shares with which the standards are distributed. While A-players have more often (9.3 and 14 percentage points more) standards EP and CE, the standard EA is more frequent (23.3 percentage points more) among the B-players.

[10] γ can be assumed as the precision parameter of the logit equilibrium and β_i/γ as the parameter of the normalized utility function.

We can interpret γ as the precision parameter of the logit choice probabilities; dividing the utility function by γ delivers a normalized utility function whose only parameter β_i/γ is lognormal distributed with $\mu - \log(\gamma)$ and σ. The distributions of β_i/γ have the same $\mu - \log(\gamma)$ value and the same σ for A- and B-players but the B-players have a smaller γ which indicates a larger *random* variance of behavior.

Table 3.3: Parameter estimates

	γ	μ	$\mu - \log\gamma$	σ	λ^{EA}	λ^{EP}	λ^{CE}	$-\log L$
A-players	3.29	2.77	1.68	0.41	0.22	0.62	0.16	425.2
	(0.17)	(0.08)		(0.07)	(0.05)	(0.06)		
B-players	1.34	1.99	1.70	0.19	0.46	0.51	0.04	274.1
	(0.20)	(0.15)		(0.11)	(0.10)	(0.10)		
A- and	2.30	2.43	1.42	0.35	0.26	0.61	0.13	434.0
B-players	(0.04)	(0.04)		(0.03)	(0.06)	(0.05)		+281.5

Parameter estimation for (3.8) and (3.9) with the utility function (3.7). Standard errors in brackets. All coefficients are highly significant ($p < 10^{-5}$) except σ for B-players. $\lambda^{CE} = 1 - \lambda^{EA} - \lambda^{EP}$.

We are not completely satisfied with this result, however. The small share of players with a conditional (CE) standard cannot explain the in-group/out-group discrimination identified by non-parametric tests, i.e. the model is misspecified. We think that the EA fairness standard and the CE out-group standard need not require strictly zero transfers. While the fairness standard EP (equality) seems to be well rooted in society, we are skeptical with respect to a *standard* of giving nothing (though actually many people give nothing), not even in cases of "self-inflicted harm"[11]. Therefore we introduce, instead of zero standards, variable standards $f_{EA}X$ (X =prize) and $f_{CE}X$ (for out-group players) in the utility function (3.7).

The estimated parameters are reported in Table 3.4. The separate estimation for A- and B-players again significantly improves the log-likelihood score with respect to all criteria ($p = 2 \cdot 10^{-12}$ in the likelihood ratio test). The same is true when we compare the scores of A-players and B-players with and without the variable fairness standards. In the likelihood ratio test we get $p < 10^{-9}$ in both cases. In addition, the frequencies based on the model with variable fairness standards and on the parameters in Table 3.4 are in good accordance with the empirical frequencies of transfers (see Appendix 3.A). They might be further improved by introducing prominence (integer number transfers). Because of

[11] Think of the biblical Parable of the Lost Son (Luke 15, 11-32).

Table 3.4: Parameter estimates with flexible standards f_{EA} and f_{CE}

	γ	μ	$\mu - \log \gamma$	σ	f_{EA}	f_{CE}	λ^{EA}	λ^{EP}	λ^{CE}	$-\log L$
A-player	3.95 (0.48)	3.07 (0.14)	1.68	0.42 (0.06)	-0.77 (1.85)	0.22 (0.01)	0.21 (0.05)	0.27 (0.08)	0.52	403.6
B-player	0.91 (0.22)	1.52 (0.31)	1.61	0.61 (0.16)	-4.64 (5.51)	0.27 (0.04)	0.33 (0.26)	0.00 (0.39)	0.67	252.1
A- & B-player	2.07 (0.26)	2.40 (0.14)	1.68	0.47 (0.06)	-0.68 (0.37)	0.23 (0.02)	0.24 (0.04)	0.23 (0.08)	0.53	417.3 +265.9

Introducing variable fairness standards $FS^{EA} = f_{EA}$ and $FS^{EA} = f_{CE}$ (out-group standard). Standard errors in brackets. All coefficients except f^{EA} and, for B-players, also λ^{EA} and λ^{EP} are highly significant ($p < 0.01$). $\lambda^{CE} = 1 - \lambda^{E}A - \lambda^{EP}$.

the restricted number of B-winners, however, we did not want to extend the number of parameters.

We find now – in accordance with the non-parametric tests – the majority of players deciding conditionally, i.e. showing in-group/out-group discrimination. They feel an obligation to help also the out-group losers, however with a mild reduction of their standard of transfers to a quarter $(0.22, 0.27)$ of their income instead of a third as in the case of in-group losers. The share of players with an ex post (equality) standard is estimated as 27 percent for A-winners and 0 percent for B-winners, although in the latter case with a large standard deviation. This is understandable because the conditional decision makers and those with an ex post standard are, in particular in the case of B-winners, not very different.

Surprisingly there are negative fairness standards in the group with an ex ante standard which make zero transfers almost certain[12]. The large standard error is due to a very flat maximum with respect to variations of f_{EA}. The log-likelihood value for $f_{EA} = 0$ is, however, 270.3 for B-players which is significantly more than 252.1. Therefore the correct standard error is large but certainly smaller than 3.59. The usage of bootstrapping for an alternative determination of the standard errors is difficult because of the long computation times for the determination of maximum likelihood estimations. Similar arguments apply in the case of A-players ($-\log L = 406.1$ for $f_{EA} = 0$) and for the joint estimation of A and B-players ($-\log L = 427.4 + 276.0$ for $f_{EA} = 0$). Our conclusion is not that there is really such a norm of taking away large sums from losers (if this were possible) but that people with negative f_{EA} are strong unconditional supporters of the idea that everybody who had had his chance should care for himself[13].

[12]For A-winners with a fairness standard $f_{EA} = -0.77$ we get prob(transfer $= 0) > 0.99$ in the case of two losers of the same kind as well as in the case of one A- and one B-loser. For B-winners with $f_{EA} = -3.80$ the corresponding probabilities are even larger.

[13]The elder brother of the Lost Son is strictly opposed to his fathers forgiving and joyful welcoming of the loser. He might be interpreted as having an EA-standard. His father, on the other hand, indicates that he is discriminative (CE-standard), telling his elder son " everything I have is yours" (Luke 15, 31). The enthusiastic welcome, however, shows that the younger son need not fear really severe discrimination.

Such a standpoint could also be expressed by the norm $f_{EA} = 0$ and a large precision parameter for this group. Adopting this idea we might ask whether also the conditional standard f_{CE} which is not far from the equality standard 1/3 should be substituted by 1/3 (thus we have an EP standard) and whether there are different precision parameters for all three cases. Estimating γ_{EA} and γ_{CE} (in addition to γ) instead of f_{EA} and f_{CE} leads, however, to increased negative log-likelihood scores (424.3 for A, 256.3 for B and 429.7 + 266.8 for the joint estimation of A and B). Thus no uniform definition and interpretation of parameters seems to be possible and we stick to the estimation in Table 3.4 where we interpret f_{CE} as a different standard of giving and f_{EA} only as a substitute for a high precision parameter[14]. For the application of variable EA standards to the data of Cappelen et al. (2013) see Appendix 3.C.

3.6 Conclusion

The main regularity in Tables 3.1 and 3.2 is that risk averters (A-players) strongly favor risk averters and that risk seekers (B-players) weakly favor risk seekers. This pattern is also found in a regression analysis (which can be found in the appendix) which controls for the influence of gender and faculty. The result is further supported by the estimation of social utility functions which reveals that the majority of individuals favor others who have taken same risk-choice over those who took a different action.

We find similarities and significant differences between A- and B-winners in our analysis of behavior in the framework of a random utility approach. A- and B-winners are rather similar with regard to transfers conditional on their type. The players with EP standards are anyway assumed to be identical and the seemingly large difference of f_{EA} for A- and B-players makes almost no difference in terms of behavior. Also players who use a conditional standard are similar: In both groups the standard for in-group players is 1/3 of the prize and for out-group players 1/4. The real difference is the frequency distribution of standards. While A-players consist of 1/5 players with EA standards and 1/4 with EP, there are no B-players with EP standards and 1/3 with EA standards. In addition, with 1/2 of A-players but 2/3 of B-players being estimated as having the conditional standard, there seems to be a correlation between risk preferences and social preferences as our more risk averse subjects are more often characterized as making transfers unconditional of lottery choice and are less often characterized as having an ex ante standard that implies no transfers to losers whatsoever. Also, the relatively large share of players with an uncondi-

[14]In a mixed approach with a precision parameter γ_{EA} and a fairness standard f_{CE} we get, in the case of B-players, $\gamma_{EA} = 11$ (std.err.= 6.4) and otherwise parameters as in Table 3.4.

tional ex ante (equal opportunity) standard among B-players shows that many people take high risks without expecting solidarity.

The different CE fairness standards and the different frequencies of fairness standards in the population are the major differences to Cappelen et al. (2013), which may be explained by the different nature of the redistribution in the two papers: while Cappelen et al. (2013) investigate redistribution of aggregate income (in real situations by taxes and social insurance schemes) our frame and focus is the voluntary transfer of income from "winners" to "losers" (within the family, among friends, and by private welfare).

Further support for a conditional standard comes from the participants' comments. Naturally, A-winners accuse B-losers of "irresponsible" behavior. In their free comments, 33 of 73 A-players did so[15]. Only one of the 35 B-players expressed this opinion, though. Therefore, behavior seems to be denounced as irresponsible only if it is riskier than one's own. In addition, 9 (out of 35) B-players explicitly remark, that B-losers should get more transfers because they are more risk-loving (i.e. like themselves). This condensed report about the free comments seems to indicate that in-group favoritism/out-group aversion is differently strong between A- and B-players. A-players condemn the decision of B-players more often and more fiercely than vice versa. Thus we may ask whether there are more differences between B-players and A-players than those which we have identified in our paper[16].

We think that it is worthwhile to look for more differences in further studies. In a world beyond our simple model there may be more agreement about the question when risk takers should be called irresponsible (risk loving car drivers) or beneficial for the society (entrepreneurs with innovative products or processes).

[15] They do not always use the term "irresponsible" but they express their opinion that the B-players should not have chosen such high risk.

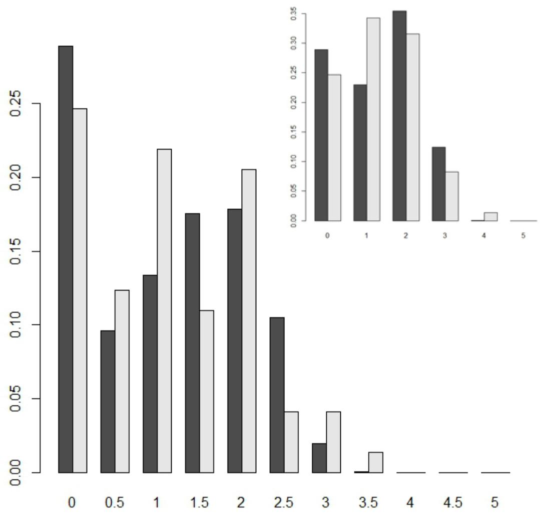
[16] Neither do A- and B-players differ significantly with respect to their share of women or economists. In the follow-up study by Lübbe and Bolle (2011), however, differences according to a personality test are found.

Appendix

3.A Predictions of the model

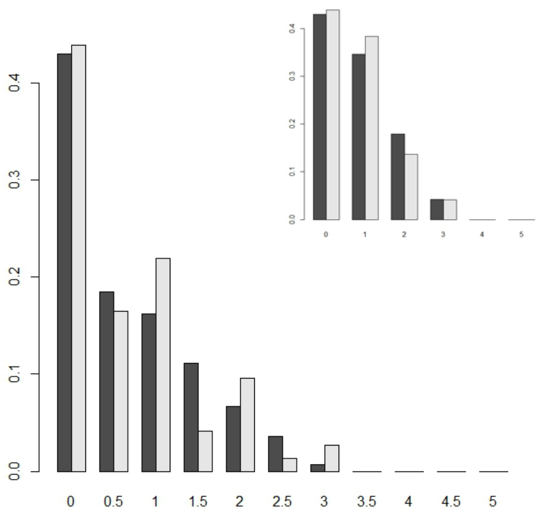
In the following Figures 3.A.1 to 3.A.8, transfers predicted by the model and the estimated parameters of Table 3.4 (black) are compared with empirical transfers (grey). As integer numbers i are more prominent, in the windows frequencies of $i+0.5$ and $i+1$ are aggregated under $i+1$. In the case where sole winners were confronted with one A-loser and one B-loser the transfers x and y are presented as marginal distributions and not as distributions of (x, y) because then 73 (35) data points would have to be distributed on a – at least – 11×11 (21×21) matrix.

Figure 3.A.1: Frequencies of A-winners' transfers to two A-losers



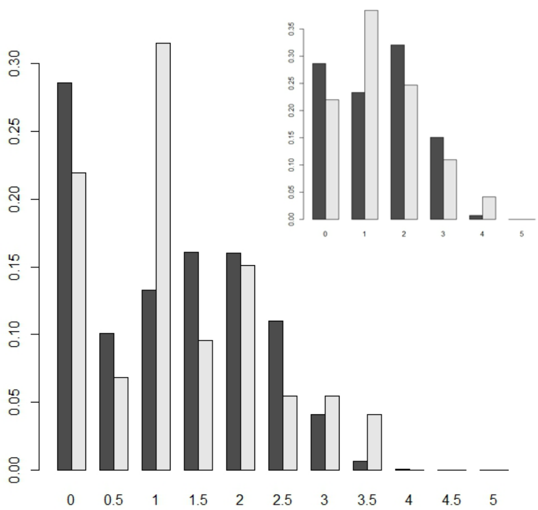
Notes. N = 73. Top right figure shows result for aggregation to integer values.

Figure 3.A.2: Frequencies of A-winners' transfers to two B-losers



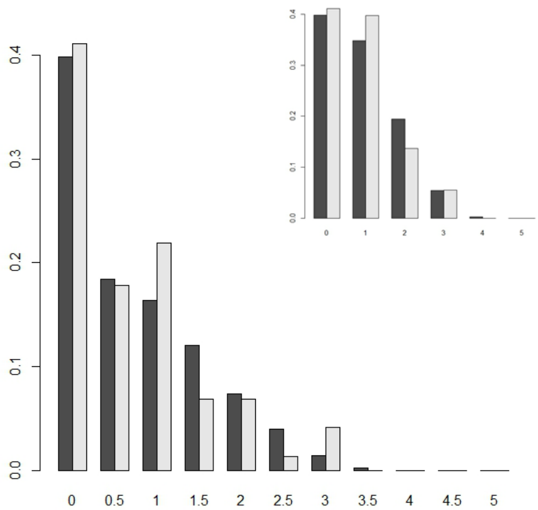
Notes. N = 73. Top right figure shows result for aggregation to integer values.

Figure 3.A.3: Frequencies of A winners' transfers to an A-loser (mixed losers)



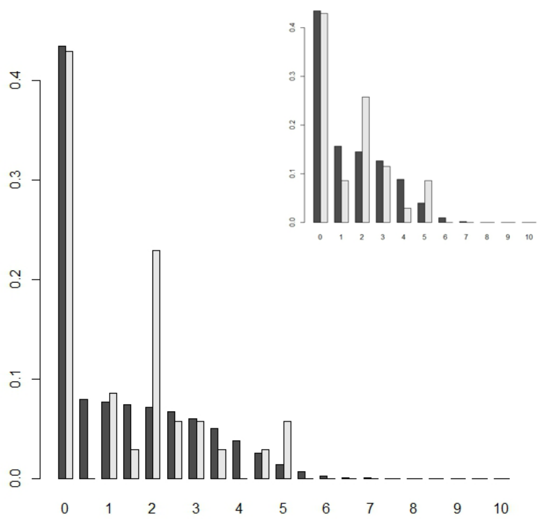
Notes. N = 73. Top right figure shows result for aggregation to integer values.

Figure 3.A.4: Frequencies of A winners' transfers to a B-loser (mixed losers)



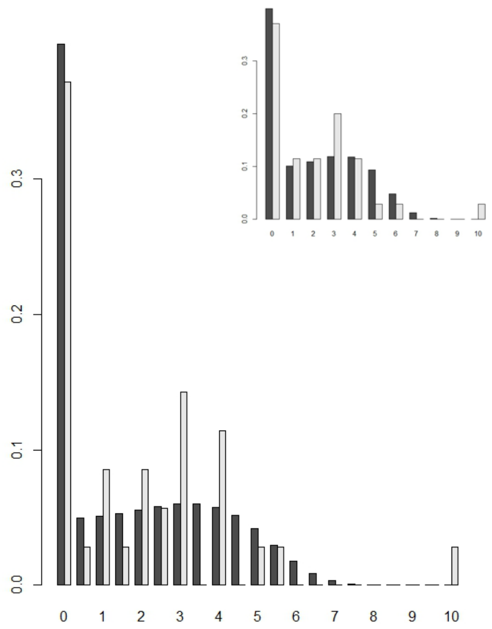
Notes. N = 73. Top right figure shows result for aggregation to integer values.

Figure 3.A.5: Frequencies of B-winners' transfers to two A-losers



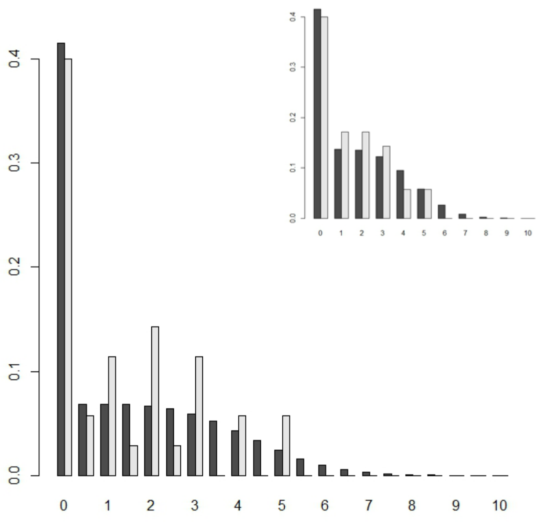
Notes. N = 35. Top right figure shows result for aggregation to integer values.

Figure 3.A.6: Frequencies of B-winners' transfers to two B-losers



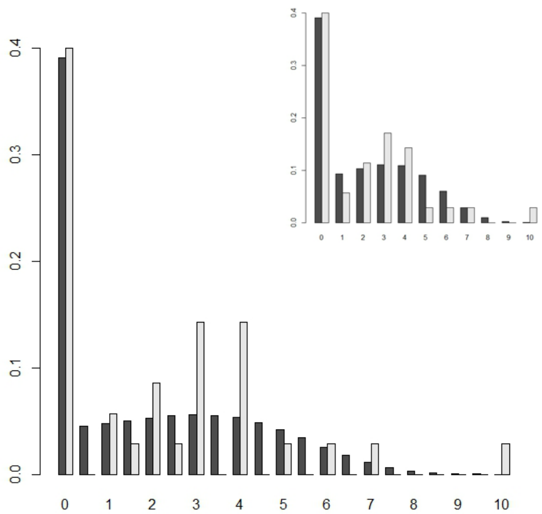
Notes. N = 35. Top right figure shows result for aggregation to integer values.

Figure 3.A.7: Frequencies of B winners' transfers to an A-loser (mixed losers)



Notes. N = 35. Top right figure shows result for aggregation to integer values.

Figure 3.A.8: Frequencies of B winners' transfers to a B-loser (mixed losers)



Notes. N = 35. Top right figure shows result for aggregation to integer values.

Table 3.B.1: Regression analysis of absolute transfers

	constant	$\mathbf{1_W}$	$\mathbf{1_{Econ}}$	$\mathbf{1_{AB}}$	$\mathbf{1_{BA}}$	$\mathbf{1_{BB}}$	Adj. R^2
2 winners/ 1 loser	1.22 (0.000)	0.55 (0.01)	-0.57 (0.02)	-0.54 (0.03)	0.67 (0.04)	1.17 (0.000)	0.15
1 winner/ 2 losers (same type)	1.15 (0.000)	0.39 (0.03)	-0.51 (0.008)	-0.45 (0.03)	0.45 (0.09)	0.96 (0.000)	0.15
1 winner/ 2 losers (diff. type)	1.26 (0.000)	0.34 (0.08)	-0.46 (0.03)	-0.53 (0.02)	0.34 (0.28)	1.06 (0.000)	0.12

Regression analysis of absolute transfers from a winner to the only loser/to one of the two losers. $N = 216$. p-values of a two-sided t-test in brackets .

3.B Regression analysis

We extend our analysis by controlling for influences of individual attributes in a regression analysis with the dummy variables $\mathbf{1_w} = 1$ for women, $\mathbf{1_{Econ}} = 1$ for economics students, $\mathbf{1_{AB}} = 1$ if the transfer is from an A-winner to a B-loser, and $\mathbf{1_{BA}}$ and $\mathbf{1_{BB}}$ respectively. The first line of Table 3.B.1 shows the results for the case where there is one loser. The value of the constant, 1.22, is the average amount which a male, non-economist A-winner transfers to an A-loser. The regressions show that, compared with the male non-economist, females' transfers were on average EUR 0.55 larger and the transfers by economic students on average EUR 0.57 smaller. Also, the coefficient of the dummy $\mathbf{1_{AB}}$ is negative and significant, showing that A-winners transfer less to B-losers than to A-losers. When interpreting the coefficient of $\mathbf{1_{BA}}$ one has to keep in mind that B-winners won double the amount of A-winners, so a coefficient of zero would mean that B-winners transferred on average and in relative terms only half as much to A-losers than A-winners did. Further, the coefficient of $\mathbf{1_{BB}}$ being larger than coefficient of $\mathbf{1_{BA}}$ indicates that B-winners favor B-loser over A-losers. This group effect is stable over all winner/loser cases. Therefore, the regression analysis confirms all the results from Table 3.1 and Table 3.2.

3.C Variable norms in Cappelen et al. (2013)

We were not completely satisfied with the original version of Cappelen et al. (2013) proposal about norms. We therefore allowed one of their norms to vary and got thus a better fit and a consistent interpretation of our results. Is such a variation advantageous also in the case of Cappelen et al. (2013) results?

In their experiments two subjects i and j decided independently about risk taking or not. They got incomes y_i and y_j according to their decisions and

Table 3.C.1: Fixed and variable norms in Cappelen et al. (2013)

	λ^{EA}	λ^{EP}	ζ	σ	γ	f^{EA}	f^{CE}	$-\log L$
fixed f^{EA} and f^{CE}	0.274 (0.086)	0.411 (0.091)	3.094 (0.503)	4.378 (0.655)	15.577 (0.509)	1	1	1200.6*
variable f^{EA} and f^{CE}	0.629 (0.079)	0.233 (0.072)	3.441 (0.424)	3.192 (0.396)	24.922 (2.019)	0.0665 (0.034)	1.003 (0.017)	1150.8

Note that the estimates in row 1 are taken from Table 4 in Cappelen et al. (2013) for specification 1 and the case of stakeholders.
Remark: * Due to different approximation methods for integration we compute 1201.8.

then subject i (or a referee, which is not analyzed here) had to distribute their aggregate income $X = y_i + y_j$ between them. i's decision is assumed to be influenced by one of three norms F^k. $k = EP$ designates the "ex post" norm of an equal split of the aggregate income. $k = EA$ designates the "ex ante" norm which requires both to get the income y_i and y_j which they earned according to their risk taking decision. $k = CE$ designates a conditional norm where for subjects who have decided as oneself (who have also decided to take a risk or have also decided to take no risk) the EP norm applies and otherwise the EA norm. If the norm k applies for i and if he decides to take x_i for himself his utility is

$$V_i^k(x_i) = \gamma x_i - \beta_i \frac{(x_i - F^{k(i)})^2}{2X} + \epsilon_i$$

where γ and β_i are parameters and ϵ_i is a random variable. The β_i are assumed to be log-normally distributed with parameters (ζ, σ). In our first estimation we accepted all these assumptions. The only difference is that we have a three-person game with a corresponding extension of the utility by an additional term and that the utility function is expressed in terms of transfers x_j to j.

The suggestion in our paper is that the "ex ante" standard may not be as strict as Cappelen et al. (2013) require it to be, in particular if our co-player earned $y_j = 0$ (the only case with transfers in our experiment). We therefore set $F^{EA} = f^{EA}x_i$ and $F^{CE} = F^{EP}$ for co-players who decided as i and $f^{CE}x_i$ otherwise. The introduction of the two additional parameters f^{EA} and f^{CE} improved the fit to the experimental data in Cappelen et al. (2013) considerably (see Table 3.C.1).

Note that all norms are effective only for large enough β_i. The large parameter γ guarantees complete egoism for a large share subjects who are assigned to any of these norms. This makes the interpretation of the results and comparisons difficult.

We have shown that there is still unexploited information in the residuals of the model of Cappelen et al. (2013) and that a generalization of their utility function is successful in exploiting this information. The question remains whether these amendments are satisfactory or whether additional aspects should enrich the original classification of social norms. In any case Cappelen et al. (2013) utility function is a promising alternative to the often used altruism and inequity aversion. Its applicability should be tested in further investigations.

3.D Instructions

The following pages contain translation of the instructions of the experiment as well as the forms used to record participants' decisions. Note that the decision form for winning participants is differentiated between participants who chose lottery A and participants who chose lottery B. For the experiment, the same was true for losing participants. However, as the decision form for losers only differed in whether they had an A or B in the top left corner of the first page, here, only one version is reproduced.

General Instructions & Decision Forms

For the following experiment, you can influence your initial endowment (in Euro) by choosing between two random processes.

Random process A: With probability 2/3 you "win" Euro 10, with probability 1/3 you receive Euro 0.

Random process B: With probability 1/3 you "win" Euro 20, with probability 2/3 you receive Euro 0.

After choosing the initial endowment, groups of three are built by random choice from the attendees. If a group consists only of winners or only of losers, the game ends. If the group consists of one or two winners, each winner has the possibility to give money to the loser(s). You will be informed on the chosen alternative of the "loser", but won't get information on the choice of the second winner in case there are two winners.

You receive the money that results from your decision. If you are a loser, you receive, in addition to your initial endowment, the money the winner(s) transfer to you. If you are a winner, you receive your initial endowment minus the transfers to the loser(s).

You can collect your payoff in the time from **11.05. to 15.05.2009** in room HG 242. Please **remember your number and pseudonym!**

Number:

Pseudonym: ________________

Which of the alternatives do you choose?

Random process A: With probability 2/3 you "win" Euro 10, with probability 1/3 you receive Euro 0.

Random process B: With probability 1/3 you "win" Euro 20, with probability 2/3 you receive Euro 0.

Please check the alternative with which your initial endowment should be determined:

Random process A	

Random process B	

What do you think, how many of the attendees pick random process A. How many pick random process B.

Random process A is chosen by ________________ % the attendees.

Random process B is chosen by ________________ % the attendees.

A
Number:

Pseudonym: ________________

You arose from the random process as “winner” and you received an initial endowment of Euro 10.

(a) What would you give if there are two winners in your group and you have no information on the other winner?

Answer A: To a loser, who choose random process A,

I give __________**,**__________EUR.

Answer B: To a loser, who choose random process B,

I give __________**,**__________EUR.

What do you expect the other to transfer ***on average****? (The best estimation will be rewarded with 10 EUR, each)*

Answer A: **I expect** __________**,**__________ **EUR on average** for a loser, who chose random process A.

Answer B: **I expect** __________**,**__________ **EUR on average** for a loser, who chose random process B.

(b) What do you give if you are the only winner in your group?

Answer A: In case both losers choose random process A,

I give each of them __________,__________EUR.

Answer B: In case both losers choose random process B,

I give each of them __________,__________EUR.

Answer C: In case one loser choose random process A and the other loser choose random process B,

I give the one with random process A __________,__________EUR
and the one with random process B __________,__________EUR.

(c) Personal data

Sex:	☐ Male	☐ Female	
Faculty:	☐ Economics/Business	☐ Law	☐ Culture

Age: __________ Semester (overall): __________

In case your transfers differed between loser who choose A and loser who choose B, please comment on the reason.

B
Number:

Pseudonym: ________________

You arose from the random process as “winner” and you received an initial endowment of Euro 20.

(a) What would you give if there are two winners in your group and you have no information on the other winner?

Answer A: To a loser, who choose random process A,

I give ___________**,**___________EUR.

Answer B: To a loser, who choose random process B,

I give ___________**,**___________EUR.

What do you expect the other to transfer ***on average****? (The best estimation will be rewarded with 10 EUR, each)*

Answer A: **I expect** ___________**,**___________ **EUR on average** for a loser, who chose random process A.

Answer B: **I expect** ___________**,**___________ **EUR on average** for a loser, who chose random process B.

(b) What do you give if you are the only winner in your group?

Answer A: In case both losers choose random process A,

I give each of them ________ , ________ EUR.

Answer B: In case both losers choose random process B,

I give each of them ________ , ________ EUR.

Answer C: In case one loser choose random process A and the other loser choose random process B,

I give the one with random process A ________ , ________ EUR
and the one with random process B ________ , ________ EUR.

(c) Personal data

Sex:	☐ Male	☐ Female	
Faculty:	☐ Economics/Business	☐ Law	☐ Culture

Age: ________ Semester (overall): ________

In case your transfers differed between loser who choose A and loser who choose B, please comment on the reason.

A/B
Number:

Pseudonym: ________________

You arose from the random process as “loser” .

What do you think, how much do you get from the winner(s)?

Answer A: In case there are two winners, I receive altogether ______,______EUR.

Answer B: In case there is just one winner, I receive ______,______EUR.

In the following we would like to know **how you would have decided in case you would have been picked as a winner.**

(a) What would you give if there are two winners in your group and you have no information on the other winner?

Answer A: To a loser, who choose random process A,

I give ___________**,**___________EUR.

Answer B: To a loser, who choose random process B,

I give ___________**,**___________EUR.

What do you expect the other to transfer ***on average****? (The best estimation will be rewarded with 10 EUR, each)*

Answer A: **I expect** ___________**,**___________ **EUR on average** for a loser, who chose random process A.

Answer B: **I expect** ___________**,**___________ **EUR on average** for a loser, who chose random process B.

(b) What do you give if you are the only winner in your group?

Answer A: In case both losers choose random process A,

I give each of them __________, __________EUR.

Answer B: In case both losers choose random process B,

I give each of them __________, __________EUR.

Answer C: In case one loser choose random process A and the other loser choose random process B,

I give the one with random process A __________, __________EUR
and the one with random process B __________, __________EUR.

(c) Personal data

Sex:	☐ Male	☐ Female	
Faculty:	☐ Economics/Business	☐ Law	☐ Culture

Age: __________ Semester (overall): __________

In case your transfers differed between loser who choose A and loser who choose B, please comment on the reason.

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Selbstständigkeitserklärung

Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung meiner Dissertation benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtungen meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen.

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